2003

A systems analysis and design approach for modelling of participatory manufacturing systems.

Ruth Jill. Urbanic
University of Windsor

A SYSTEMS ANALYSIS AND DESIGN APPROACH FOR MODELLING OF PARTICIPATORY MANUFACTURING SYSTEMS

By

R. Jill Urbanic

A Thesis

Submitted to the Faculty of Graduate Studies and Research

through the Industrial and Manufacturing Systems Engineering Program

in Partial Fulfillment of the Requirements for

the Degree of Master of Applied Science at the

University of Windsor

Windsor, Ontario, Canada

2002

0-612-80515-8

ABSTRACT

Today's manufacturing enterprises are encountering unprecedented challenges: global markets, volatile demands, consumer expectations with respect to quality, convenience, and price are only a partial list. To meet these challenges, manufacturing technologies and business practices are evolving, with more emphasis being placed on teamwork, such as concurrent engineering product teams. Long term success is dependent on balancing the human characteristics, needs, and skills with the manufacturing technology and the other business elements.

A Systems Analysis and Design approach was utilized to integrate manufacturing technologies with the capabilities of human workers, in order to augment the performance of both. This research has produced a solid framework on which to build sophisticated systems analysis tools that focus on realistic factors within the manufacturing environment, such as information quantity, diversity and content; complexity (product, process and operational); task effort, employee skill sets, corporate culture and so forth.

These factors influence the human interactions within any manufacturing system environment. By considering these variables, a qualitative model was developed to capture the impact of human characteristics in a manufacturing system.

The goal of this research was aimed at understanding the effects of human worker attributes within the manufacturing system environment; hence, a model is needed to provide insights into the sensitivities of a manufacturing system. To this end, a framework has been developed which is valid for different perspectives and environments. A matrix methodology has been created that assesses the three levels of manufacturing complexity: product complexity to process complexity and operational complexity. The systematic approach has lead to the development of an objective measure of complexity, which can be used to "mathematically" show tradeoffs at each level.

A model that ties in the elements of "operational complexity" to a participatory manufacturing model has been achieved through utilizing the learning curve phenomenon. The model directly takes into consideration memory and problem solving abilities. As well,

the model also contains a weighting factor based on the available skill sets of the employees, task factors such as time duration and direct and indirect tasks, attitude and behaviour and finally, the corporate culture and environment.

The unique approach to analysing skills, tasks, attitude and culture presents relevant metrics that are based on readily available data, in particular, the corporate culture influences. The traditional method of analysing culture focuses on demographics. A fresh approach is taken in this work: using various rates of change within the workplace as a complement to the learning curve model, as the learning curve essentially models adaptation to change.

Because of the variable nature of the factors researched in this work, it is evident that various artificial intelligence techniques in combination with experimental data would be an effective approach for future contributions.

This is a very relevant topic for research. The participatory manufacturing model will complement other design tools, as its goal is to highlight sensitivities in the design stage – only the focus is not on the robustness and usability of a product, but the robustness and usability of the manufacturing process.

ACKNOWLEDGMENTS

I wish to express my sincere appreciation to two key individuals: Dr. Waguih ElMaraghy, my supervisor, and Robert Hedrick, my husband. Dr. Waguih ElMaraghy gave me the chance to pursue this research as well as continuing insight and support throughout the development of this thesis. His high standards and sweeping visions combined with a sense of humour made any conservation or task interesting, inspirational and enjoyable.

My husband, Robert, has provided unconditional support in this endeavour, as he has throughout any project upon which I have embarked.

I wish to thank Dr. Mike Wang and Dr. Robert Gaspar, my committee members, for their guidance and encouragement.

Thanks are also due to Jacquie Mummery, and the staff of the Industrial and Manufacturing Systems Engineering Department for their friendly assistance and support, and to the group members for their encouragement.

Finally, I must convey my deep gratitude to several individuals external to the academic environment, such as my fellow co-workers at Ford Motor Co., Essex Engine Plant, who have helped me in ways too numerous to mention.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1.0 INTRODUCTION

> *"Production and thereby manufacturing performance ... are conceived as a strategic weapon for achieving and maintaining competitiveness." [Feldman and Slama, 2001]*

> *"A company's manufacturing function typically is either a competitive weapon or a corporate millstone. It is seldom neutral. The connection between manufacturing and corporate success is rarely seen as more than the achievement of high efficiency and low costs. In fact, the connection is much more critical and much more sensitive." [Skinner, 1978]*

In the past, the work process has been analysed and broken down into standardized component parts, and reassembled in an efficient manner. The component parts included the human element as well as equipment. This method of scientific management applied by Henry Ford and refined by Frank Taylor in the early 1900's had served as an efficient, cost effective manufacturing model until today; this model produces wealth, but is inflexible, and reduces the human to the level of a pawn. This manufacturing philosophy was the source of inspiration for Huxley's "Brave New World" [Huxley, 1978]. In this projection of the future, every facet of life is patterned on a standardized human element – government managers assign individuals to their slot in the social and economic hierarchy.

But for the present and the foreseeable future the rules that have made this model an "ideal" have changed, and are continuing to change in an unprecedented manner. Globalization has revolutionized business. Over and above a world standard of value, modern consumer expectations include: product innovation, time to market, high quality, convenience, compatibility, and low cost. The rate and magnitude of change is unparalleled. Previously, businesses had to adapt to incremental changes that could be phased into place in a timely manner. Market variations were typically due to seasonal and economic cycles. New technologies and technological obsolescence combined with globalization has revolutionized business. There is radically intensified competition, and rapid creation of new markets. Value, quality, price, and innovative features are commodities [Tichy, 1993] and manufacturing performance, as mentioned by Feldman and Slama [2001] and Skinner [1978], must be considered as critical as innovative products. There is a need for both productivity and innovation – and the innovative approach must be expanded to include new processes as well as new products. Focusing piecemeal on each element alone will not suffice. Manufacturing systems need to adapt to new events illustrated in Figure 1.1. However to be effective, the system must balance human characteristics, needs, skills and capabilities within the technical and business environment: a multi-faceted human point of view, in conjunction with the development of technical and financial tools, is crucial for long term success. A systemic approach is presently used in some local environments or tasks (e.g. concurrent engineering), but this must be extended in manufacturing.

Dynamic Market

Technology Challenges

- Innovative Specialized Products
- Innovative Manufacturing Processes
  - Scale of processes
  - Span of processes
  - Ideal balance of equipment capacities
  - Degree of automation
  - Degree of mechanization and controls
- Product Time to Market
- Technology Diffusion
- Production Changeover and Rapid Ramp up
  - Equipment reliability
  - Process performance and stability
- Software Compatibility & Upgrades
- Hardware Compatibility & Upgrades
- Obsolescence

Business Challenges

- Economic Issues
  - Resource management
  - Efficiency
  - Product life cycles
  - Environmental Legislation
  - Return on Investments
  - Prices, Margins
- Legal Requirements
- Government Regulations
  - Local
  - National
  - International
- Skills and Tool Training
- Organizational Learning
- Dynamic Product Demands
- Staff Up/Downsizing
- Contractual Agreements
  - Supplier
  - Employee

FIGURE 1.1: TODAY'S MANUFACTURING AND BUSINESS CHALLENGES

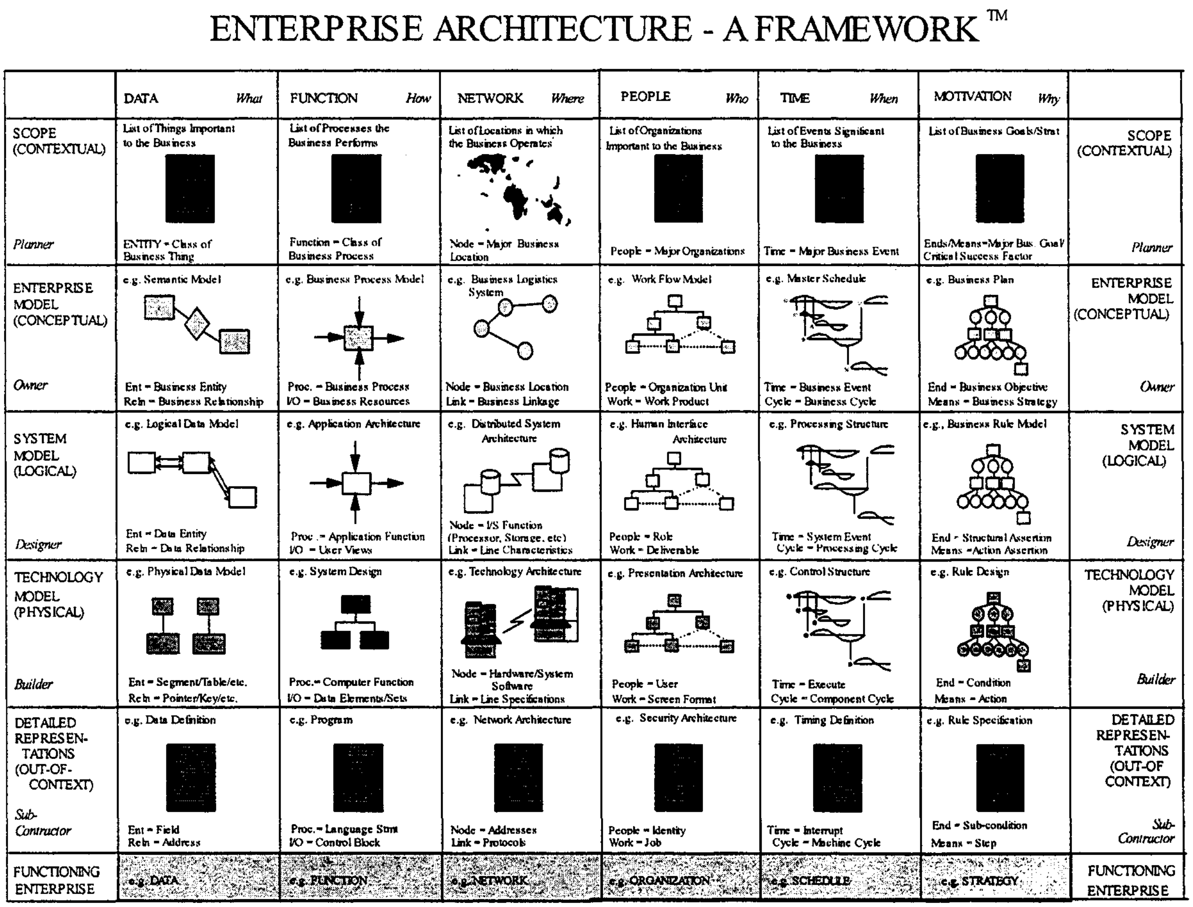
1.1 Problem Statement

The recognition of the need for a viewpoint, which includes the human element as an integral part of the modern production system, is gaining momentum in several fields of study, but is also supported by personal industrial experience. Effective implementation and use of the sophisticated technologies inherently uses some techniques to balance product and process design and other manufacturing activities but in an unscientific and non-robust manner. Typically there is a fragmented approach to manufacturing systems design today. This research is beneficial as it applies a balanced and integrated approach to addressing realistic issues: integrating and augmenting human performance in a dynamic manufacturing environment. This topic is best addressed under the discipline of Industrial and Manufacturing Systems Engineering because to be effective both the human and systems elements must work together as a whole. Product development time has been greatly reduced through sophisticated design, engineering and information systems tools; however, there are no ubiquitous equivalents in the manufacturing systems sector.

1.2 Research Objective

This research project aims at enhancing manufacturing system models with human worker attributes. This is in order to gain insights on a manufacturing system's performance for a particular configuration and environment, which is subjected to a variety of disturbances. It is proposed to integrate manufacturing technologies with the capabilities of human workers, in order to augment the performance of both. Human intentions, goals, and skills at the enterprise (conceptual), system (logical), and technical (physical) levels as defined by Zachman and illustrated in Figure 1.2 [Zachman, 2002] are clearly important factors, but have not been addressed within a quantitative modelling framework. Cooperation / collaboration / teamwork interaction as well as conflict of goals is even more complex to model, but is the reality of the workplace.

Studies in human-computer interaction, behavioural psychology, cognitive ergonomics, human performance modelling, manufacturing systems design and control theory are all part of the building blocks of a participatory manufacturing system model. The desired output of the model is a manufacturing system where the various "agents" – either machine or human – support each other, not only during normal operation but also in a crisis situation.



John A. Zachman, Zachman International (810) 231-0531

FIGURE 1.2: ZACHMAN DIAGRAM [ZACHMAN, 2002]

The modelling methodology to predict work task performance has not been qualitatively or quantitatively developed in the manufacturing environment, but inroads have been made in several fields of study. Qualitative analysis tools such as utility charts for trend analysis, normalized indices and heuristics are some of the tools utilized to create a framework for human performance factors in a manufacturing setting. Any model will not definitively predict how an individual person will behave at any given moment, but the system sensitivities and performance trends over time, for a good model, would provide valuable insights. Comprehensive information or comparisons of different design, configuration and process planning scenarios will help the decision making processes at all levels of manufacturing.

The long term goal is to able to define a mathematical model and standard performance parameters for machine utilization, defects, and work in process in combination with a human performance model. How "attitude" and other "soft" intangible parameters like complexity, memory, learning or problem solving ability are defined is not the essence of the problem for this project. The effects or *results* of these parameters need to be utilized for a "human oriented" production model. The output variables for these intangible items must be functions with respect to time and costs. This in turn can cascade into the standard production drivers (quality, uptime, machine utilization, etc.), which can be modelled by systems analysis and simulation techniques. Present simulations focus on up time or efficiency, and help determine equipment and buffer criteria based on equipment performance and job scheduling. This needs to be extended to reflect trends based on human performance variables, and how that affects the process output.

1.3 Research Approach

To develop a "balanced" performance model, as conceptualized in Figure 1.3, within a manufacturing environment, the following approach was taken. First a literature review was performed which covered manufacturing environments, business strategies, and the systems infrastructure to support these manufacturing concepts. This is presented in chapters two, three and four. Another literature review was conducted to cover social / psychological aspects of human behaviour and learning theory, and is presented in chapter five, with detailed information in Appendix A. Chapter six contains a review of human performance modelling presently under development. Interestingly, the U.S. Military has recognized the need for supportive man-machine systems well in advance of industry. A pictorial overview of the literature review is presented in Figure 1.4. For the purposes of brevity in this document, only a snapshot of the literature review for chapters two, three and four are presented, as the information presented within them are more "common knowledge" in the manufacturing engineering environment.

A systems approach was utilized in this research. First, an Integration DEFinition 0 model (IDEF0) was created based on the literature review and personal experience to capture the essence of an agile enterprise using reconfigurable manufacturing technology, and is presented in full in Appendix B. IDEF0 modelling techniques are used as they are an effective, structured, graphical tool that was specifically developed to model decisions, actions, and activities of a given system, either at an overview or at a detailed level. The next step is to define and develop indices that influence human performance characteristics and reflect the manufacturing environment. This is presented in chapter seven.

The manufacturing environment indices aim at the product diversity, product, process and operational complexity. The human performance variables include factors such as worker availability, learning ability, skill level and the task type, and the corporate culture. Obviously, there are many interactions. In chapter eight, a participatory model is introduced which ties together these various loose ends - the "learning curve" theory is used as a base model. A qualitative analysis is performed to identify the nature of the various interactions. The goal is to gain insight of the system performance and sensitivities when considering human characteristics.

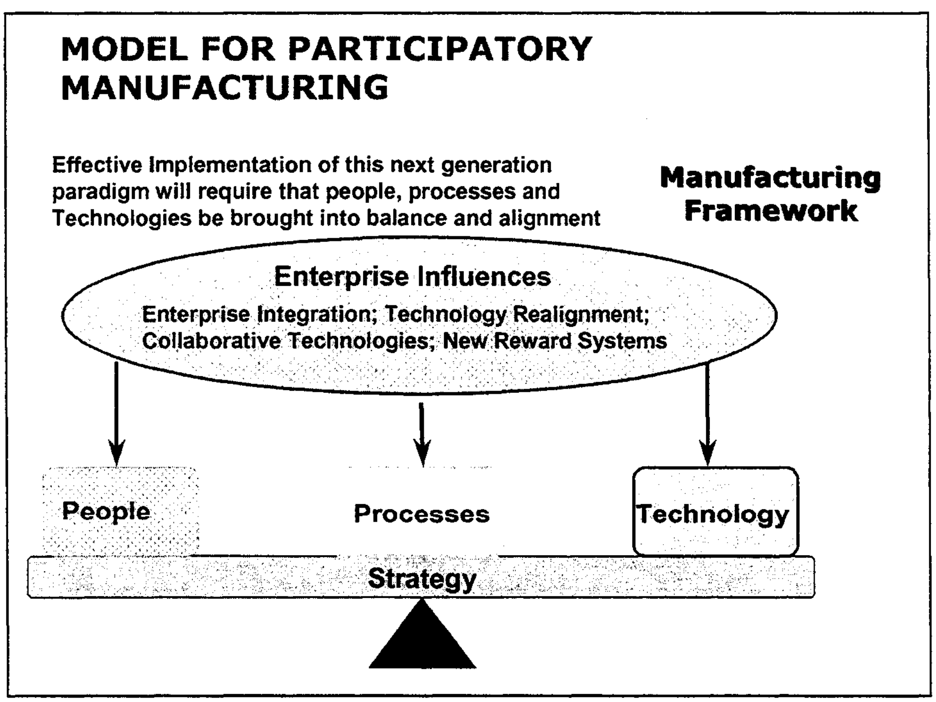


FIGURE 1.3: BALANCED MANUFACTURING SYSTEM

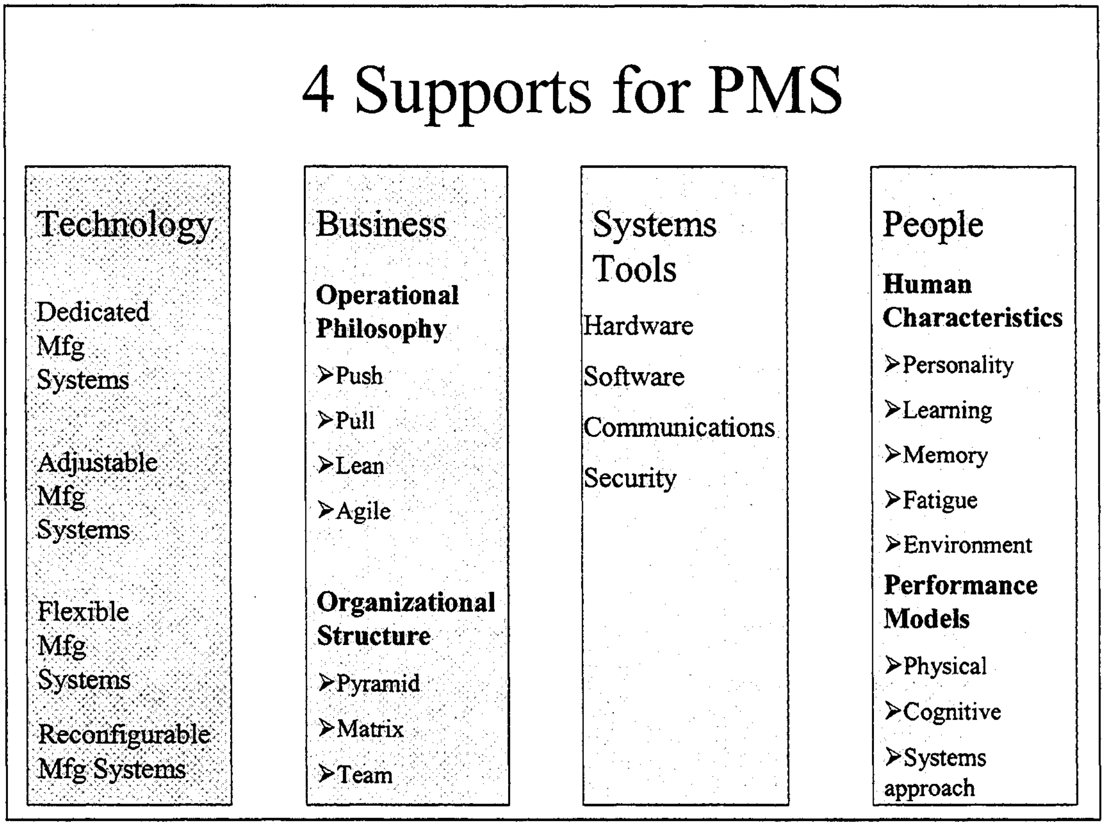


FIGURE 1.4: FOUR SUPPORTS FOR PARTICIPATORY MANUFACTURING SYSTEMS

The research based on integrating technology with the capabilities of human workers is challenging but critical to assessing the long-term success of any manufacturing enterprise. Dynamic human-computer interaction is a way of life today: whether programming a cell phone, microwave, 5-axis CNC machine or performing queries on a Web based search engine. Research that balances the capabilities of several elements, both physical and human, is very relevant to the outcome of any large manufacturing enterprise. Each system is unique, and must be defined and developed with the end users' functions and abilities in mind.

2.0 MANUFACTURING ENVIRONMENTS

2.1 Introduction

The evolution of the manufacturing environment is illustrated in Figure 2.1, and is summarized in Table 2.1, which is presented at the end of the chapter. The four general manufacturing systems are dedicated manufacturing systems (DMS), adjustable manufacturing systems (AMS), flexible manufacturing systems (FMS) and reconfigurable manufacturing systems (RMS) [Glardon and Zhang, 2001]. The business strategies are discussed in chapter 3.

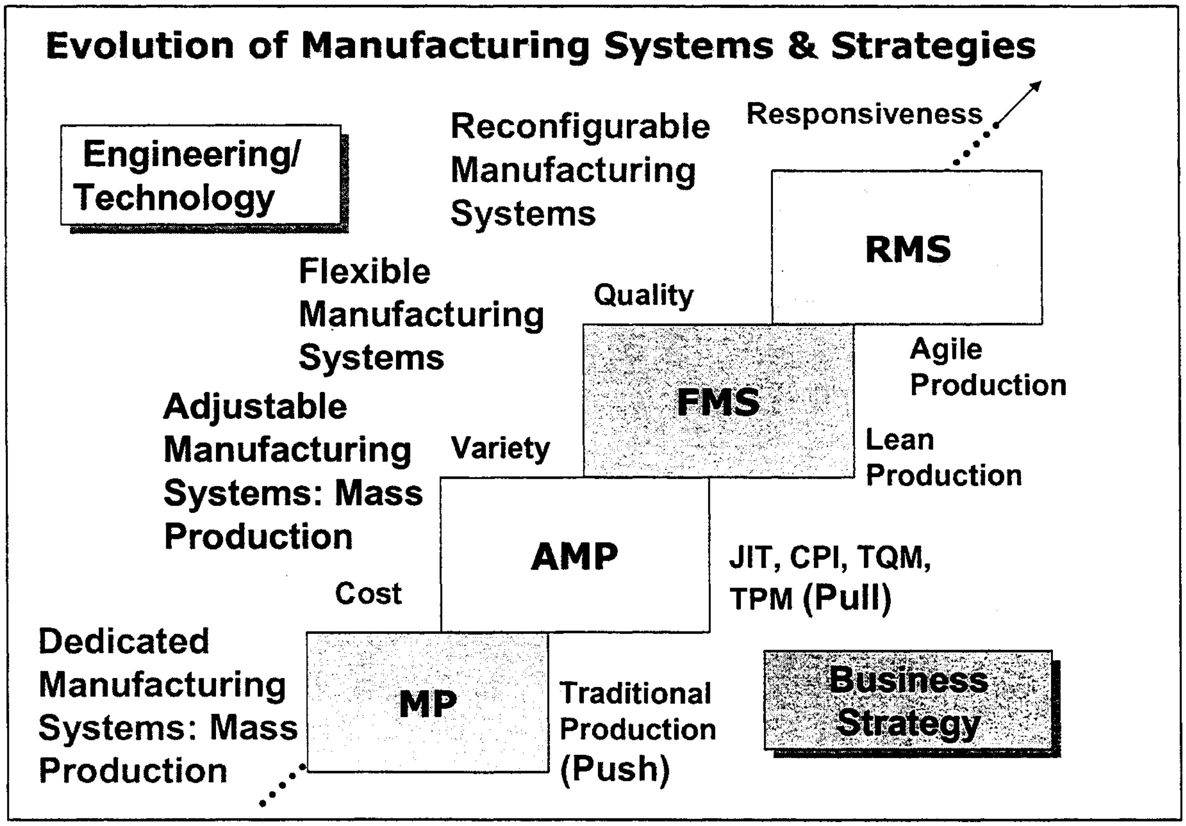


FIGURE 2.1: EVOLUTION OF MANUFACTURING SYSTEMS AND STRATEGIES

2.2 The Evolution of Manufacturing Environments

2.2.1 Dedicated Manufacturing Systems

Dedicated manufacturing systems consist of "hard tooling" - high performance, specialized, single purpose machines. Each component (jigs and fixtures, spindles, tools, dies, manipulators, etc.) is customized and optimized to perform a specialized work task within a specific time envelope. Intricate and precise components are manufactured at high volumes (engine and transmission component machining, assembly and testing, vehicle assembly, etc.) with a minimum of skilled labour. Typically there is a fixed time interval within a workstation, and to transport the part or assembly from one fixture or station to the next. This equipment is designed around a unique product, or there is very little product variation within a family of parts. The equipment is rigid, and the focus is a limited production mix, mass production and the economies of scale over a long planning horizon.

2.2.2 Adjustable Manufacturing Systems

Adjustable manufacturing systems (or flexible transfer lines) have the same basic properties as dedicated manufacturing systems in that there is a fixed time interval to perform the work function and the focus is on mass production and economies of scale. However, the base units consist of standardized designs and modular components, and each unit executes a specific function, rather than producing a part. Specialized machining heads, fixtures or other components mount on the base units. The base units and modules are assembled into a final unique configuration for a particular product or product family. Standard controls and mechanical interfaces impart reduced ramp up times for machine commissioning and product changeovers. Multi-spindle head changers, shown in Figure 2.2, and multi-position shuttle units, etc. allow greater variation in component design and manufacturing, as there is some limited product flexibility within the system.

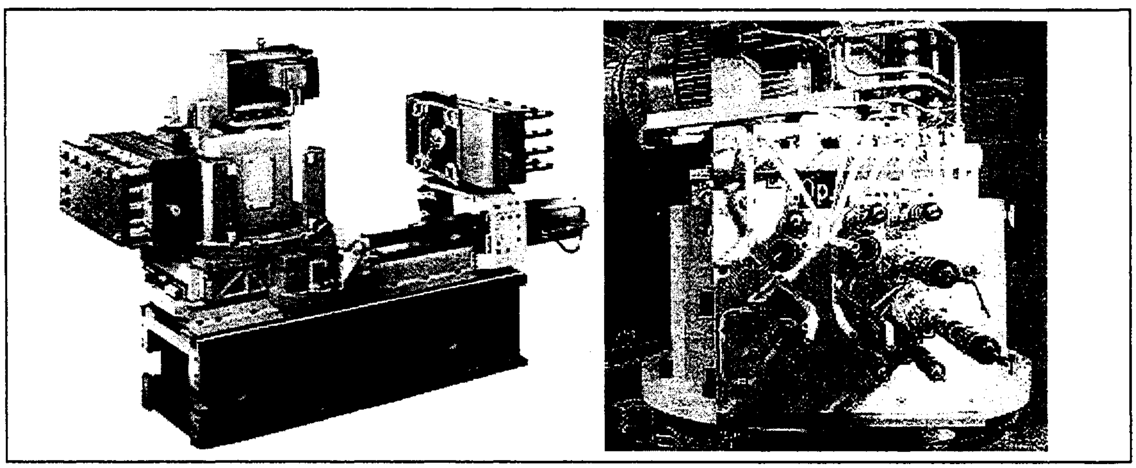


FIGURE 2.2: CROSS HUELLER ® HEAD CHANGERS [HÜLLER HILLE, 2001]

2.2.3 Flexible Manufacturing Systems

Flexible manufacturing systems consist of general purpose and special purpose programmable machines such as robots, automatic guided vehicles (AGV), CNC machining centres, coordinate measuring machines (CMM), automatic storage and retrieval systems (ASRS), and so forth under a central control. A flexible system is adaptable and versatile, and is capable of adjustment or adapting without a substantial modification of the structure by using interchangeable fixtures, tools, manipulators, etc. Hence, a flexible manufacturing system can accommodate design and engineering changes on a more timely and cost effective manner than either the dedicated or adjustable manufacturing system. The functionality of flexible equipment is based on general parameters. While the general nature of these parameters allows a wide range of product mixes (dissimilar parts) and volumes, it also inherently results in complex set up procedures and processes. This makes it difficult to troubleshoot equipment problems, and track defects. This equipment is expensive to purchase, configure and maintain, and is optimal for small batch runs of a wide variety of products. There is presently much research and development with respect to implementation and optimizing flexible manufacturing systems due to the complex nature of the system configuration modelling, analysis, and simulation.

2.2.4 Reconfigurable Manufacturing Systems

Reconfigurable manufacturing systems optimize capabilities for each business opportunity, and represent step beyond dedicated and flexible manufacturing systems. The focus of RMS is rapid production change, and is deemed optimal for short term and low effort adaptability [Heisel and Michaelis, 2001]. With the decreased product life spans combined with the volatile market, this is certainly an admiral goal.

But what is RMS exactly? At this time, there is no clear, specific definition for what constitutes RMS, but there is one common concept: RMS consists of modules, which provides the ability to reconfigure technologies, organisations, or enterprises in response to rapidly changing circumstances. *RMS is both **scalable** and **transformable**.* Research appears to be equally divided in three different areas:

- Modular philosophy,
- Configuration management, and
- Flex – plus

An overview of each area is discussed below.

2.2.4.1 Modular Philosophy

The specific focus for modular design is at the base level of the manufacturing process: the equipment. An oversimplification would be stating that the modular philosophy concentrates on equipment specific "part swapping", enabling different functions by different configurations. This is not the case: the modular philosophy is an old concept that is being rejuvenated by modern, sophisticated tools for design and analysis. *Complementing the physical precision machine tool, assembly, and metrology components are libraries of these elements, which link into solid models, FEA and simulation techniques, optimization algorithms and other high-level systems analysis tools to aid in process planning, validation, execution and support.* This philosophy has been extended beyond the traditional mechanical domain into reconfiguring the machine tools and robots themselves, robot manipulators, sensors, hardware, software, and communication systems.

University of Michigan has design projects focusing on reconfigurable machine tools and spindles [Koren and Ulsoy, 2001]. Intelligent fixturing concepts are being developed at Berkeley [Wagner et al, 1997] and University of Toronto [Sela et al, 1997]. Research consortia such as HIPARMS (Highly Productive And Reconfigurable Manufacturing Systems) [HIPARMS, 2001] and ARMMS (Agile Reconfigurable Manufacturing Machinery Systems) [ARMMS, 1999] are investigating modular control technology and machine flexibility with interchangeable mechanical modules. Figure 2.3 illustrates a sample of modular philosophy research endeavours.

2.2.4.2 Configuration Management

Like the above philosophy, configuration management requires analysis of the existing manufacturing elements; configuration management encompasses the large-scale components or the complete spectrum of manufacturing systems: resources, structures, layouts, logistical and organizational concepts, as well as supply chain relationships, are modified and adapted dynamically. The system is rebalanced (scaled up or down, or resources redistributed) at the macro level based on new information within a given planning period [Hiromi et al, 2001]. This can occur within an enterprise or between several enterprises (inter-enterprise relationship), as decentralized, autonomous and geographically distributed manufacturing networks are the norm today. In either case, information is a critical resource, and teamwork and cooperation are central requirements.

RECONFIGURABLE MANUFACTURING RESEARCH

Sample of University Research

University of Toronto

- Intelligent Fixturing

University of Michigan

- Reconfigurable Machine Tools Components
- Tool changer power spindle
- Multi-spindle head
- Reconfigurable Machine Tools
- Reconfigurable Monitoring
- Multi-sensor technology

Auburn University

- Reconfigurable Smart Components
- Sensors, Hardware, Software

Berkeley

- Fixture-Net

Sample of Research/Industry Consortia

ARMMS (Agile Reconfigurable Manufacturing Machinery Systems)

HIPARMS

NIST – TIMA

CAMI

OCASA

Sample of Commercial Endeavours

Gilman; Masco

Configuration Management

University of Michigan

- Impact of System Configuration on Performance
- Planning, Economic Modelling

FIGURE 2.3: RECONFIGURABLE MANUFACTURING RESEARCH

A systematic approach is needed to deal with these complex and large scale issues whether it is optimally reallocating resources within an enterprise (transforming multiple internal operations by repositioning of equipment, material transport systems, buffers, personnel, etc.) or identifying the "right" collaborative partner(s) and integrating them across all collaborating enterprises [Wiendahl, 2001; Hiromi, 2001; Smirnov, 1999; Davidrajuh, 1999; Deng et al, 1999, 2000]. Both scenarios deal with analysing and optimizing complex, dynamic combinations, which depend on the prevailing economic forces at a particular instant of time. Modelling and problem solving methods such as artificial intelligence, Petri nets, genetic algorithms, constraint-based problem-solving, constraint-based heuristic search, etc. are being developed to support human decision-making.

As the information flow is exchanged synchronously between several networks, hardware and software platforms and operating systems, fast, accurate, and robust information is the foundation for successful results.

2.2.4.3 Flex-Plus

New manufacturing systems with greater flexibility than the traditional general purpose machines are being developed. This creates new manufacturing opportunities. A sample of the leading edge technologies is listed below.

(1) Rapid prototyping is a method of creating a prototype part without any hard or soft tooling. Stereolithography, fused deposition modelling, laser sintering are a sample of commercially available rapid prototyping technologies.

(2) Flex form tooling methods include "hydro-forming", which consists of a female die and a pressurized hydraulic bladder to form sheet metal; elasto-forming, which consists of a male punch and an oil-filled forming cavity; die-less forming and hydro-die forming. These techniques require little or no hard tooling.

(3) Multi-spindle, multi-turret lathes have been developed which allow five axis milling as well as turning operations. These machines allow simultaneous machining of multiple work pieces, which are not necessarily the same part.

(4) Flexible robots systems have been developed with include: robotic assembly of modular tooling systems [Kilman, 2001]; Stanford has developed a unit modular reconfigurable robot – the Polypod.

(5) Hexapod machining centres and robots are an alternate method of fixturing, machining and assembling components.

(6) Research is conducted to create intelligent machines [Katz et al, 2001; Colding, 2001], which are able to overcome unexpected problems. Sources of uncertainty could include unexpected events such as internal component failure or an external disturbance such as an unpredictable environmental change. Another hurdle to

overcome is incomplete, inconsistent or unreliable information. These machines require perception, cognition and execution subsystems.

The goals of this new technology are to allow for rapid optimization of new product and process design options without investing in "hard tooling", minimizing the need for fixturing and set-ups, and adapting to process or product changes.

2.2.4.4 Common Elements

Although there seems to be at least three unique directions for reconfigurable systems, all the above schemas have several common elements. Their focus is to introduce optimal, controlled changes, minimize ramp up times, reuse resources, and maintain the integrity of the configuration throughout the product life cycle. Information systems and flow is critical for success. Data must be accurate, complete, and up-to date, and available on a real time basis. The manufacturing issues are complex, and the modelling and simulation systems access several knowledge bases, analysis tools and decision support systems to aid in effective design, planning, process validation and execution, monitoring and diagnostics. Not only are the engineering and process systems linked, but also the financial systems (accounting), purchasing, marketing, sale and distribution and human resources systems are linked, and provide the goals and constraints for any planning period. There are a large number of interdependencies that must be managed within a reconfigurable manufacturing system.

2.3 Summary and Conclusions

Each manufacturing technology was revolutionary in its time. High volume, dedicated equipment introduced standardized processes that could be performed with a large percentage of the workforce being both uneducated and unskilled. Through the economies of scale costs were reduced, which ensured both long runs and constant demand. However, as customers became more sophisticated and more competitors entered the market, some level of product differentiation became necessary; hence, the introduction of adjustable manufacturing systems. When the level of variety and the quality expectations continued to increase, flexible manufacturing systems became vogue.

System	Characteristics	Properties	Production modes
DMS (Dedicated Manufacturing System)	Special purpose machines Hard Tooling Fixed control system Path fixed conveying system Multi-tools and multi-direction machining	Rigid Efficient Sequential operations Parallel processing	High volume Long runs Constant demand Stable design Minimal product variations
AMS (Adjustable Manufacturing Systems)	Standardized base units and modules "Special purpose flexibility" Turrets and orbital units, Shuttle units, rise and fall units Mixture of Hard and Soft Tooling Limited adjustable control system Path fixed conveying system Multi-tools and multi-direction machining	Moderate flexibility Modular, standardized components Efficient Sequential operations Parallel processing **Reduced launch curve during product changeovers – base modules have been commissioned during original launch**	High volume Long runs Constant demand Minimal product variations Narrow range of work pieces
FMS Flexible Manufacturing System	General purpose machines Soft Tooling Programmable control system Flexible conveying line Single tool and unilateral machining Multiple paths for machining, welding, assembly, etc.	Multi-product **Small batch production** Accommodate design and engineering changes more easily than a DMS or AMS configuration **Large initial capital expenditure**	Large family of work pieces Wide variety of dissimilar parts
RMS	Ability to arrange modules for different objectives Balance between dedicated and flexible manufacturing systems Enables rapid production change for either volume variations, or product mix	Mass customization Accommodate rapid process and product engineering changes Scalable Transformable	Customized products

TABLE 2.1: SUMMARY OF MANUFACTURING TECHNOLOGIES ADAPTED FROM GLARDON AND ZHANG [2001]

This technology required large capital expenditure, as the equipment was purchased with flexible elements in order to accommodate potential changes of multiple products. However, flexible manufacturing systems require sophisticated information system tools, and a skilled workforce as well as educated support personnel. Reconfigurable manufacturing systems can be manipulated to adapt to change for mass customization. The modular nature of reconfigurable manufacturing systems allows for reuse. To be effective, reconfigurable systems require sophisticated information systems at multiple levels, and a skilled workforce, which cooperates and collaborates on a dynamic basis.

As the manufacturing technology has grown, so has the need for increased skill sets, continuous learning, open communication, employee involvement and continuous innovations. Understanding the nature of the factors that influence human performance is beneficial in any environment, but as the systems become more complex and the market demands more volatile, this becomes even more critical; hence, the need for a manufacturing system model that considers human factors over and above ergonomics → the Participatory Manufacturing System.

3.0 MANUFACTURING STRATEGIES

3.1 Introduction

The previous chapter dealt with the manufacturing environments and processes used to make the part – this chapter focuses on the manufacturing strategies or the business philosophies of production and organizational structures. For any manufacturing environment and finished good, the fundamental production control decisions are:

1. How much should be produced?
2. When should the goods be made?

Many facilities produce multiple products from a multi-stage process. Random disturbances such as equipment breakdown, broken tooling, cycle time variations, resource availability, consumer demand, and so forth must be resolved as they occur. Managing the above criteria to maximize profit and minimize costs through effective resource utilisation is the challenge when addressing the above questions.

One approach to scheduling is to forecast the quantities to be produced, and generate production schedules based on the anticipated sales. From this forecast demand, components are ordered and schedules are generated. To manage a predetermined schedule, variations of manufacturing capacities, manpower, available standard production hours, lead-time of raw materials, etc. are absorbed by work in process (WIP) inventory buffers. Inventory instantaneously meets downstream demands; consequently, disruptions at any point are localized. Buffers are used to decouple operations and smooth out disturbances. Throughput is rigorously monitored at specific pay points, and schedule/process changes are made only if necessary. Work in process is "pushed" through the system. While this system allows plants to operate at capacity because the uncertainty of supplies, capacity, process reliability, etc. has been reduced, it has the disadvantage of creating periodic oversupply, as well as increasing inventory carrying costs.

The alternative scheduling technique is "pull" or Just In Time (JIT) manufacturing. Production is based on actual customer demand. Feedback from the succeeding operation triggers a production request from the preceding operation. This occurs for each operation within the production process. As production demand originates from the final operation and proceeds to the initial operation, the whole production process is linked together. To manage this technique, a basic requirement is a timely relay of orders to the production facility, and an optimized production scheduling process to fulfil those orders. Process stability, equipment reliability, and co-operation between management, employees, and suppliers are critical elements to ensure effective management of this production control strategy. Figure 3.1 illustrates the push and pull strategies. Hybrid production control systems have emerged which incorporate key points from both the push and pull philosophies; techniques from each are used where appropriate.

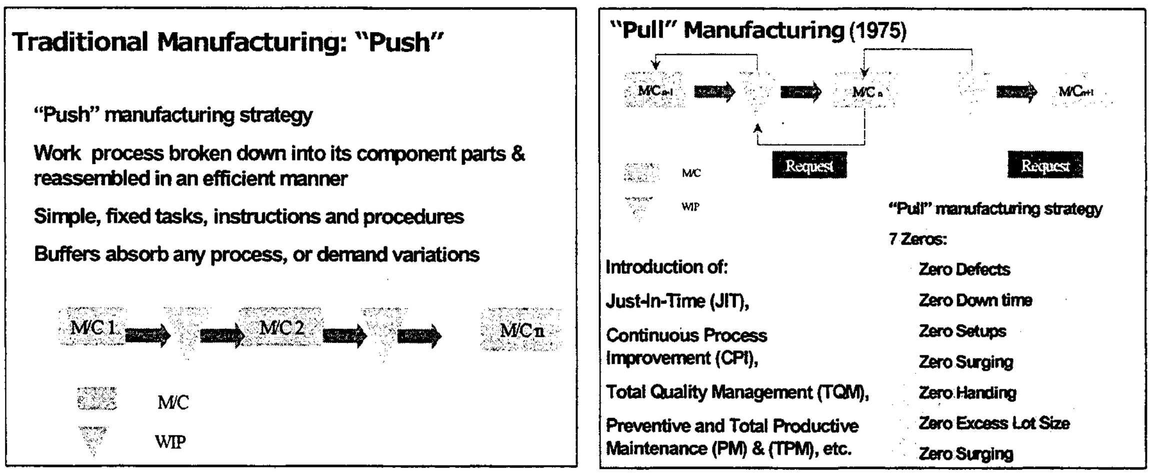


FIGURE 3.1: PUSH AND PULL MANUFACTURING STRATEGIES

The manufacturing environment does influence the production control strategy to some extent, and this must be recognized. From the two basic production control philosophies, lean manufacturing and agile manufacturing have materialized, and are described in the next sections. These strategies have a greater influence on process design and the manufacturing environment, but are management philosophies. They fundamentally influence scheduling, job routing, and work in process, but their influence is extended beyond the shop floor. The manufacturing technology, environment and organizational structure is designed and configured to support the particular manufacturing strategy used.

3.2 Lean Manufacturing

The focus of lean manufacturing is to "do more with less". The manufacturing systems are pushed to continuously reduce inventory, lead-time, overhead cost reductions, and so forth which mirror the seven zeroes of the "pull" strategy. However a lean enterprise extends into all elements of the manufacturing plant: accounting, management practices, machine design, and support functions in general. A lean manufacturing strategy encourages flat organizational structures. Reduced management levels encourage initiative and information flow to highlights defects, human errors, equipment abnormalities, and organizational deficiencies. Similar to the "push" strategy, smart tools that focus on standardized work, standardized processes and procedures are used in conjunction with design for manufacturing, design for quality, and design for reliability (both product and process) principles.

Lean manufacturing has limited capabilities to handle change, uncertainty and unpredictability, as compared to an agile enterprise, which is designed to survive and thrive in a volatile environment. Both JIT and lean manufacturing encourages employee participation, but it also leads to downsizing, and increased workloads for those who remain [Hormozi, 2001]. Agile manufacturing, a concept introduced by the Iacocca Institute, is a post-lean production paradigm. An agile manufacturing enterprise develops and exploits capabilities to use knowledge and information for a long term, sustainable, competitive advantage. The ability to easily adapt strategies, structures and processes to a company's market positioning and its business environment is the fundamental mindset for the agile manufacturing system.

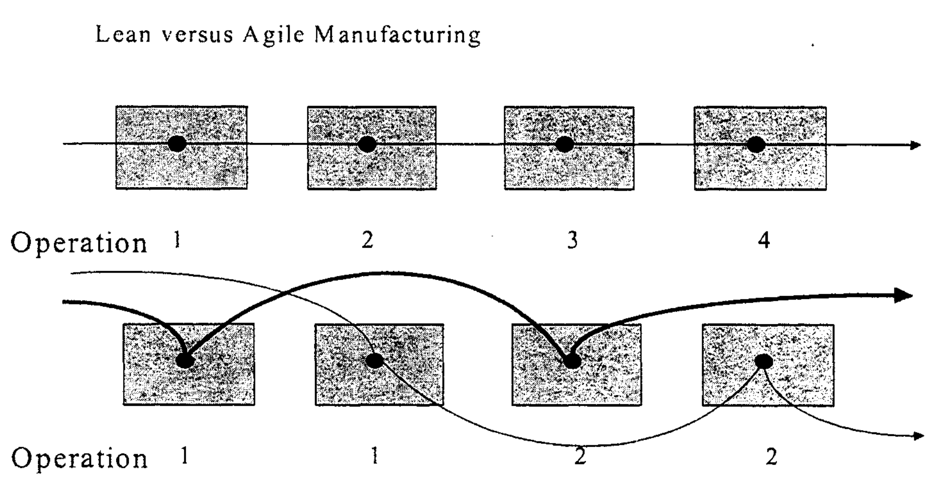
3.3 Agile Manufacturing

The "Agile Manufacturing" strategy was introduced in the 21st Century Manufacturing Enterprise Strategy report [Nagel et al, 1991], and is not a mature philosophy at this time. Agile Manufacturing is a "holistic" concept which links processes, departments, organizations and business relationships in cooperative endeavours to adapt to new markets, volatile market demands, and changing technologies [Dove, 1995]. Agile systems adapt smoothly to change. Although there are no specific definitions as to what agile manufacturing is, there are clear concepts of what it is not. Agile manufacturing is not

Total Quality Management (TQM), Business Process Reengineering (BPR), lean or flexible manufacturing or computer integrated enterprises. A comparison of lean manufacturing versus agile manufacturing at the process level is shown in Figure 3.2.

Agile manufacturing organizations have a fundamentally different way of doing business – they change continuously with time in a cooperative, creative and robust manner.

A proactive management style is necessary for successful agile management [Owusu, 1999]; employees must be empowered to make decisions without having to continuously defer to upper management. Decision making must be driven to the lowest appropriate level. Employee involvement and development is critical for success; hence the need for both good communication and robust information systems [Owusu, 1999; Hormozi, 2001 Weston, 1999] to complement the relevant technologies. To show a physical analogy of the interconnecting links for the agile manufacturing philosophy, Meredith and Francis [2000] introduced the concept of the "agile wheel", shown in Figure 3.3.



Lean enterprise → part stops at each machine sequence. There is one set of tools, fixtures, and operating procedures.

Agile enterprise → flexible routing options, complete with tooling and fixtures that can adapt to multiple configurations. The engineering, support systems and the work force within the enterprise have a foundation on which to be able to effectively respond to changes on an "at-needed" basis.

FIGURE 3.2: LEAN VERSUS AGILE MANUFACTURING ADAPTED FROM ZELINSKI [2001]

The agile wheel illustrates the balance between the business strategies and practices, the actual manufacturing processes, the links between business partners, the customers and suppliers and the human resources within any agile enterprise. All spokes must be in place in order for the agile wheel to function. Employee involvement is critical. Agile manufacturing is equally dependent on systems and the intelligence and resourcefulness of the employees. Multi-skilled flexible people, capable of rapid problem solving and decision-making are key to the success of the agile manufacturing strategy; consequently a non-hierarchical environment (such as product teams) that encourages trust, motivation, involvement, and continuous training must be developed and maintained.

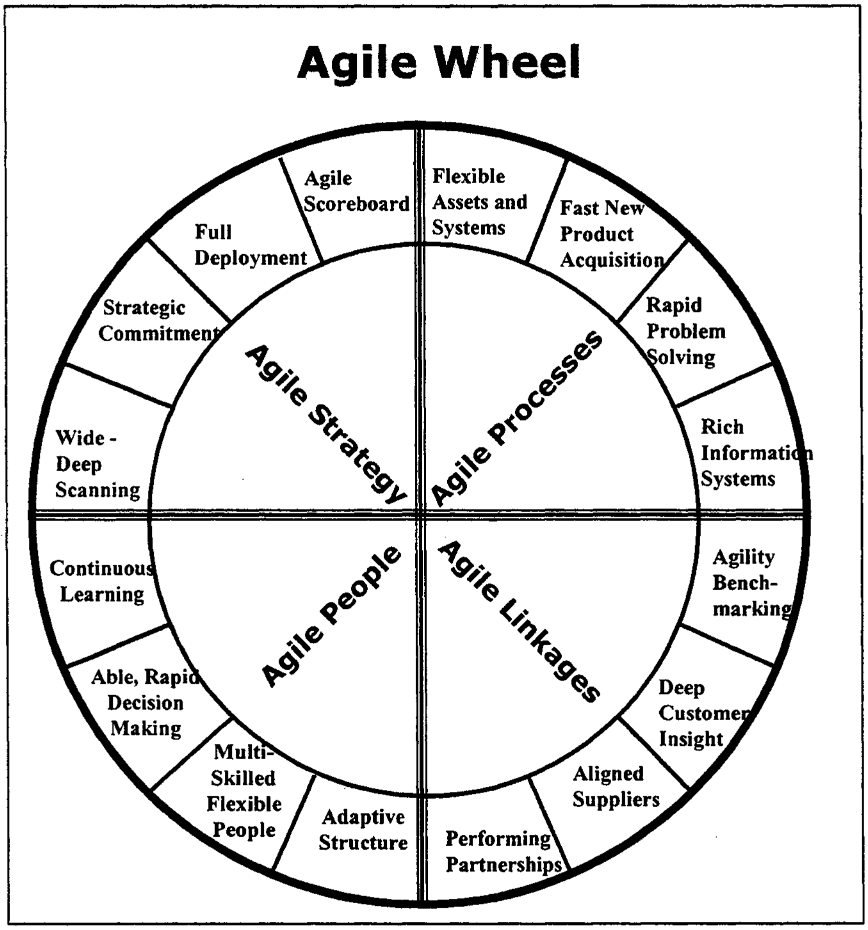


FIGURE 3.3: AGILE WHEEL [MEREDITH AND FRANCIS, 2000]

3.4 Agile Manufacturing with Reconfigurable Technologies

The ability to effectively deal with the changes and overcome related disturbances could be most successfully realized with an agile manufacturing strategy within a reconfigurable manufacturing environment. Unforeseen, volatile, unexpected changes at any level of an enterprise are happening continuously. The agile manufacturing strategy complements any and all of the three reconfigurable manufacturing system environments discussed above. This combination has the scope to effectively:

- Enable product and process creativity necessary for an aggressively competitive market.

- Rapidly evaluate alternatives, trends and risks [IMTI, 2000].

- Bring a new product into production that is responsive to the needs and wants of the end user or customer (100% on-time delivery performance, low cost, rapid response, exactly to spec, product features, etc.) [IMTI, 2000].

- Bring a new discrete part or subassembly to production with minimal recurring costs that achieve (or surpass) a target cost [IMTI, 2000].

- Bring a new product (or subcomponent) into production rapidly, with minimal nonrecurring cost.

- Quickly propagate changes to all affected parties [IMTI, 2000].

- Ability to predict production parameters such as operating cost [Allen, 2001; Glardon and Zhang, 2001; Amico et al, 2001, Feldman, 2001] or quality at the product design stage.

- Minimize the need for specialty design fixturing, tooling and software [Wiendahl, 2001, Nagel et al, 1991],

- Reduce process lead times, and ramp up times.

Successful implementation of all the resources depends on the quality of interactions between them. This leads to the necessity of understanding human characteristics and modelling the effects of human participation beyond treating employees as sophisticated general purpose machines.

The next section discusses the influence of the organizational structure, and the next chapter discusses the information tools necessary to accomplish this.

3.5 Organizational Structures

The manufacturing technology and the business philosophy are two elements of an enterprise: the third basic element is the organizational structure. Within the organizational structure there is a division of labour, a chain of command to distribute responsibility and authority, "flows" up and down the organizational ladder, standard operating procedures and explicit rules to conduct business. In essence, the organizational structure defines how job tasks are formally divided, grouped and coordinated. The five aspects of an organization are:

- job tasks or work specialization
- departmentalization
- chain of command
- span of control
- formalization

An organizational chart pictorially displays the formal organizational structure: the departments and job titles, lines of authority and the relationship between departments.

There are three basic organizational structures: the pyramid, matrix and product team, and two methods for delegation of authority: centralized and decentralized. The principles governing the division of tasks and responsibilities varies from enterprise to enterprise, but typically the "closer" the employee is to the final product, the need for physical labour and technical skills increases.

3.5.1 Pyramid Structure

The classical organizational chart is pyramid structure, which could be either tall or flat, as illustrated in Figure 3.4. Departments are divided by function, product, geography or customer type.

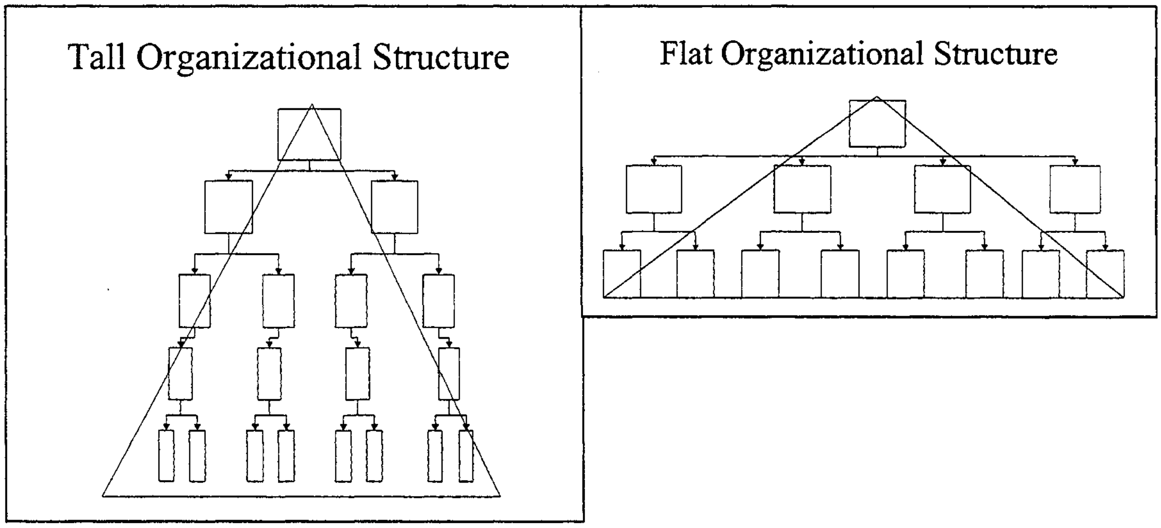


FIGURE 3.4: PYRAMID ORGANIZATIONAL STRUCTURES

In a tall organizational structure or a traditional bureaucracy, there are well defined jobs at each level. At the lower levels, the job tasks are both specialized and repetitive. It is uncomplicated to train new employees; within a short period of time the employee should be proficient with the required tasks. There is very little mental work in these typically menial tasks, both at the production levels and in the lower management levels. This organizational structure complements the dedicated equipment technology. There are clear lines of authority, and bounds on responsibility. Information generally flows between adjacent levels. The focus on specialization leads to standardization of equipment, tools, procedures, designs, etc. and allows for the efficient distribution of the human resources within the enterprise. Usually, the control is "centralized" – the authority and decision making is concentrated in the upper management levels. Although effective, this organizational structure encourages barriers between the departments. Business decisions focus on optimizing the departments, not the organization as a whole. There is little or no cross pollination between departments, and typically communication occurs at the upper levels. These issues generate redundancy – or waste – within the enterprise. To deal with some of the negatives of the pyramidal organizational structure, the "Flat' structure has evolved. The flat structure has fewer layers: each manager has a wider span of control, and less time with individuals. Control is decentralized: i.e. the decision making authority is delegated to the lowest organizational level capable of making a competent decision. This structure forces the communication channels to open, reduces departmental barriers, and requires relevant information to be made readily available. This is necessary within a "pull" or lean manufacturing environment.

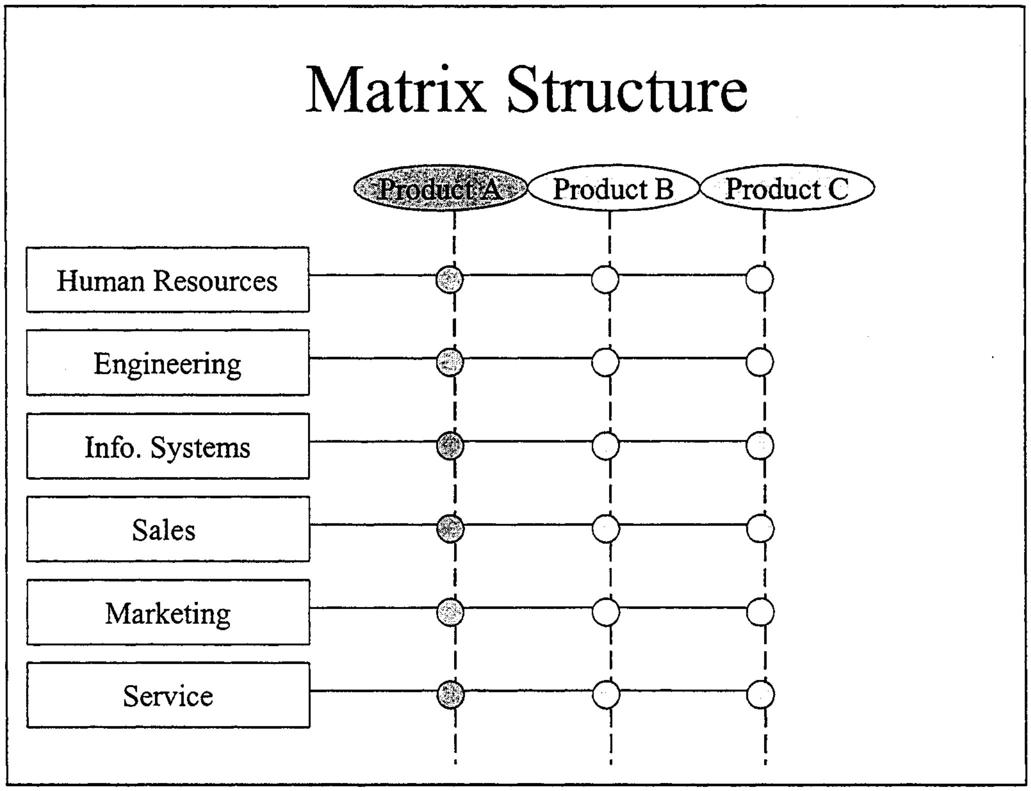


FIGURE 3.5: MATRIX ORGANIZATIONAL STRUCTURE

3.5.2 Matrix Structure

The pyramidal structure is one dimensional, the matrix structure is two dimensional (Figure 3.5) and consists of a complex network of reporting. With the matrix structure, several initiatives are pursued simultaneously, and there is input from several perspectives. The matrix organization generates optimal decisions for the enterprise as opposed to one department. The matrix structure encourages creativity and innovation. Knowledge is shared, and there is less duplication of effort and redundancy. However, as approval to act comes from several (and maybe conflicting) lines of authority, it takes longer to make and act upon a strategic decision. As well, the individual roles and responsibilities are undefined, and it is difficult to maintain a balance between several lines of authority, especially in a conflict situation.

3.5.3 Product Team Structure

An intermediate structure between the pyramid and the matrix structure is the permanent product team or the strategic business unit structure. Permanent cross functional teams actively promote cross pollination between departments / businesses (Figure 3.6). Like the matrix organization, this structure should promote objective, optimal decisions with respect to the available resources and the proposed strategies. This leads to reduced design and manufacturing costs, but unlike the matrix organization, on a timely basis.

Most large enterprises use more than one type of structure to improve efficiency and to adapt to the business needs.

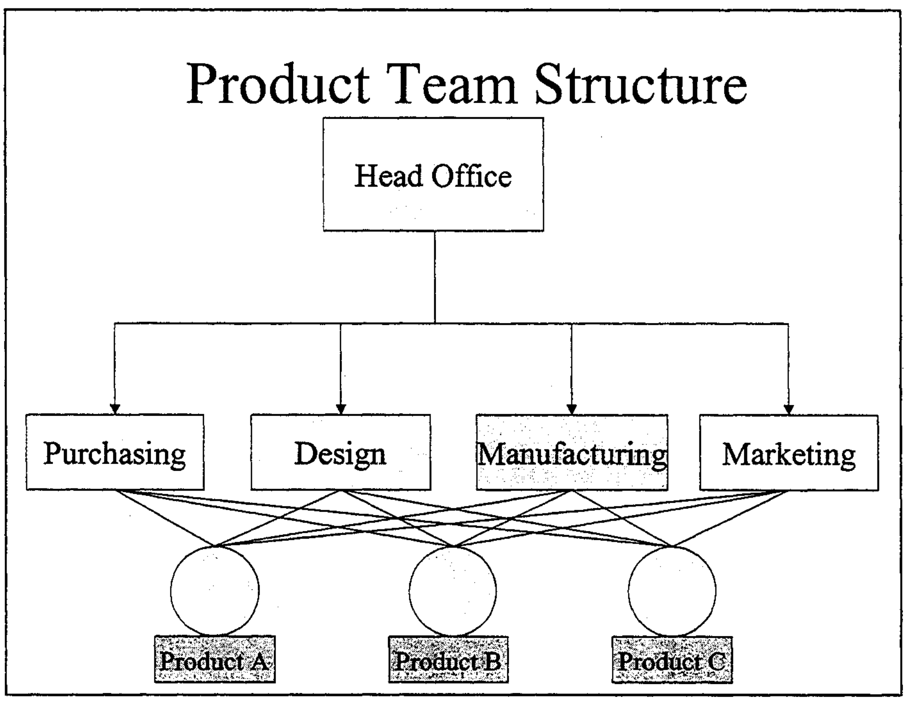


FIGURE 3.6: PRODUCT TEAM ORGANIZATIONAL STRUCTURE

3.6 Summary and Conclusions

To summarize, push system output is independent of sources of variation within the process, and is much more efficient than pull system output. The push management focus concentrates on throughput efficiency to reduce piece price burden, consequently excess safety stock exists. Pull systems are very sensitive to normal process variation, as well as machine breakdown. The management philosophy in tandem with pull systems is to focus on the root causes of the variation and reduce or eliminate them, as opposed to introducing more WIP, hence the development of the seven zeroes strategy (Figure 3.1). For a pull system, the health of the system is more important than the health of a single profit centre unit typical in a push system.

To change between one method of operation to another is unrealistic, as it may be ineffective depending on the nature of the business. However, using advantages from both philosophies where appropriate can reduce inventory costs without jeopardizing the throughput efficiency, and this has led to the hybrid approach. Lean manufacturing has evolved from the pull strategy, and extends the production control influences into both the process design and the organizational structure (flat pyramid structure). With a traditional manufacturing strategy, simple rules are devised via ergonomic and task analysis methodologies and management monitors the activities. Typical for a tall pyramid organizational structure or bureaucracy, this is a closed and contained environment with systematic controls and a specific chain of command. The traditional method is inflexible, and reduces the human to the level of a pawn. The agile manufacturing strategy is the complete antithesis of this. This strategy depends on the trust, cooperation, creativity and flexibility of the employees, departments, and the business organizations that form a partnership. In essence, a dynamic leveraging of skills and resources occur, which can only exist in an environment, which promotes dynamic cross functional product teams or business units and decentralized authority. Significant advances have been made integrating product and process related models with performance and cost models. By doing so, the test / evaluate / modify phases for any product, part or subassembly and its related processes can be significantly reduced [Nagel et al, 1991]. This allows an enterprise to transform itself with each business opportunity and consequently, survive and thrive in uncertain times. Table 3.1 from Hormozi [2001] summarizes the evolution of manufacturing strategies from "craft" production (pre-industrial revolution) to today.

Human performance has the most impact in an agile production enterprise; however, it also has a heavy influence in a lean production enterprise. Although the chart below indicates that craft and agile production require highly skilled employees, it is not a one to one comparison. The knowledge base for a skilled employee in a modern manufacturing enterprise is beyond the skilled trades level associated with craft production. The items that are highlighted in Table 3.1 have a direct influence to the success of an enterprise, and are not based on physical skills, but cognitive skills or the "intelligence capital"; hence the need for a participatory modelling system that considers factors over and above process equipment variables and layout.

Industry Objectives	Craft Production	Mass Production	Lean Production	Agile Production
Emphasis on waste elimination	Medium	Low	High ★	High ☆
Degree of production leveling	Low	Medium/ High	High	Flexible
Degree of organizational communication	High	Low	High ★	High ☆
Sensitivity to customer demands	High	Low	Medium ★	High ☆
Need for ***skilled employees***	***High***	***Low***	***Medium*** ★	***High*** ☆
Degree of cooperation between companies	Medium	Low	Low	High ☆
Piece cost of small runs relative to large runs	Same	High	Medium	Same
Lead times for existing products	Varies	Short	Short	Short
Degree of Product Marketing Required	Low	High	High	Low

TABLE 3.1: COMPARISONS OF PRODUCTION STRATEGIES [HORMOZI, 2001]

Missing from Hormozi is the influence of the organizational structure. Both craft and mass production have centralized control – authority is concentrated in upper management or by the owner, while lean and agile manufacturing have decentralized controls – to be effective in these environments, authority must be delegated to the lowest level capable of making a competent decision. As well, the craft, mass and lean production environments typically have a pyramid organizational structure – either tall or flat, but the strength of the agile enterprise is to be able to form product teams dynamically to address each situation in a suitable fashion.

4.0 SYSTEMS FOUNDATION

Today's leading edge manufacturing enterprise is based on a collaborative process, and knowledge integration is the foundation for all levels of decision-making. Robust, accurate, complete, up-to-date information flow must occur seamlessly through all levels of an enterprise [IMTI, 2000, Davidrajuh, 1999]. This is a significant and complex challenge. There are several roadblocks to making this the modus operandi. Several contemporary issues are listed below.

1. Internal work structures provide barriers to free flow of information [Weston, 1999]. This could be due to the corporate culture, where several unwritten rules, policies, procedures and methodologies exist, or due to contractual reasons.

2. The written or electronic documentation is inaccurate, obsolete or out-of-date, or there are undocumented procedures.

3. With the global economy, there are multiple cultures, practices, policies and behaviours.

4. Proprietary information formats are difficult to integrate, such as

- software
- databases
- user interfaces
- hardware
  - process equipment and controls
  - computer
- communications
  - protocol
  - physical interface

5. A cost intensive, massive effort is required to implement and integrate information systems that share real time manufacturing data throughout the manufacturing

enterprise. Specialized training and support is also required to maintain these systems.

6. There is redundant data due to the proprietary systems limitations, and specific user needs. Ironically this in turn leads to incomplete or conflicting data records within the system; each dataset may be complete within a narrow application, but there is no single, complete, up- to-date record.

7. Information is dispersed between many locations.

8. Direct factory floor manufacturing systems focus on the operation of production equipment and on the control of processes. They do not communicate directly with front office information systems dedicated to accounting, planning, and other business activities (and typically not with design and engineering systems).

9. There is a lack of hardware, software and communication standards. Some existing standards are not a complete solution (i.e. an IGES file translated between two different platforms does not ensure 100% data integrity).

10. Integration, support and phasing out of obsolescent software and hardware is capital intensive and risky.

The systems integration issues reduce down into two main challenges:

- Interoperability, and
- Acquiring and representing valid information such that confident predictions can be made.

4.1 Human Elements

Although the information technology is essential to the success for today's complex, integrated, multi-disciplinary manufacturing environment, the most significant resource is the human resource. Huxley's "Brave New World" [1978] imagines an environment where people are conditioned to love what they are predestined to do. A system of human eugenics, development and conditioning designed to standardize the human product and facilitate management tasks, complements the traditional manufacturing environment in Huxley's future. In reality, the complete opposite is necessary. By drawing on the creativity and intelligence of all employees, innovative solutions will emerge in response to volatile economic environments. This leads to new engineering challenges: designing systems where the human-machine systems cooperate and support each other. This extends beyond physical ergonomic tools into cognitive ergonomics, info-ergonomics, Human-Machine [Yamada and Vink, 2000] or holonic systems.

To this end continuous training is vital; education on new technologies and processes will enable employees to better carry out their tasks. Management support needs to focus on cooperation, collaboration, and reducing the hierarchical structures. Facilitating cooperation among people must take precedence over enforcing compliance, and initiative must be valued more than obedience. Communication and trust are the keys: management must communicate goals and constraints to the workforce, and the workforce must be enabled to provide feedback and input to management, regarding the means to reach these objectives and goals [Owusu, 1999]. Another prerequisite is to focus on the identification of the skill sets required to perform tasks at any level of an enterprise, and the development of the appropriate tools to enable employees to operate efficiently across organizational and functional boundaries, either independently or as part of a cross-functional team [Meredith and Francis, 2000; Nagel et al, 1991, Ross, 1994].

HUman-MAchine Coexisting Systems (HUMACS) focuses on pursuing a practical methodology in establishing optimum relationships between the human factors and manufacturing facilities [Yamada and Vink, 2000]. The relevant problems are mobilizing human power, preserving and enhancing skills, and exploiting the information technology to resolve socio-technical problems. Establishing a human centred production system uses automation to free humans from simple, repetitive physical tasks. Development of a participative simulation environment to integrate technology, human performance and social factors is being pursued in order to support companies in creating an optimal organizational structure.

Another approach towards realizing more flexible management is presented by Sugimura [2000]. International cooperative research is focusing on developing a holonic model for autonomous distributed control in the machining environment with respect to planning scheduling fixture set-up, and assembly.

4.2 Conclusions

Agile manufacturing has emerged as the future business strategy. One of the key elements is "agile processes", which consists of flexible assets, fast new product acquisition, sophisticated problem solving tools, rapid problem solving, and robust, transparent, rich information systems [IMTI, 2000; Nagel et al, 1991, Weston, 1999]. Although there is no one specific definition for reconfigurable manufacturing systems, each element (modular philosophy, configuration management and flex-plus) complements the agile manufacturing approach. Further development of information technology is required to facilitate seamless, secure and reliable information flow. Intelligent modelling and analysis systems assist in rapidly testing, evaluating and validating the optimal processes within a given planning period. Product and process models link into performance and cost models. This will sustain the business enterprise, as modern businesses need to be continuously re-evaluated and reconstructed in order to increase overall organizational efficiency and effectiveness. The specific reconstruction could focus on the equipment, process or facility resources, or identifying the right collaborative partners and managing the supply chain relationships.

In all the above cases, the management philosophy must support creativity, continuous training, employee involvement and empowerment. Human workers are the most adaptable part of the system [Ahanotu, 1998]. ***The most reconfigurable resource is the human resource.***

5.0 HUMAN CHARACTERISTICS

5.1 Introduction

Human performance varies greatly and in the realm of engineering has mainly been studied in the physical domain: ergonomics (strength, flexibility, coordination, speed, accuracy, reach, etc.). The goals are optimization of a required movement, or task sequence with respect to time and physical constraints. This has expanded into cognitive ergonomics: studies that focus on performance in a systems (IT) environment, i.e. time required to use the program, the probability of making mistakes, and the performance of the users as discussed in chapter 6.

Performance characteristics are linked to behaviour, learning, memory and the immediate environment of the individual; hence, these must be considered in a "human-engineering" simulation model. But what are the factors that constitute behaviour, learning and memory? A brief overview is presented in this chapter.

5.2 Behaviour and Personality Theories

> *"Most people of course, whatever they may say, do not in fact want a scientific account of human nature and personality at all.... Hence they much prefer the great story-teller, S. Freud, or the brilliant myth-creator, C.G. Jung, to those who, like Cattell or Guilford, expect them to learn matrix algebra, study physiological details of the nervous system, and actually carry out experiments rather than rely on interesting anecdote, sex-ridden case histories, and ingenious speculation."*
>
> - *Hans Eysenck,* Psychology Is About People [1972]

5.2.1 Introduction

Personality is the individualized or distinctive and characteristic patterns of thought, emotion, and behaviour that define an individual's personal style of interacting with the physical and social environments. There is a wide spectrum of theories as to what constitutes and influences personality. Biological theories link body type to personalities; behavioural theories link the environment to personalities. Psychodynamic theories focus on the unconscious and the irrational forces while the humanistic approach rejects all the above, and focuses on self-will. Six common theories are summarized [Baldes, 2000; Boeree, 1997; Heineman, 1995; Neill, 1999; Bull, 2001; Psychology Course Notes for HP603, 1999]. They are:

- Body Type Theory
- Psychodynamic Theory
- Humanistic Theory
- Behaviour and Social-Cognitive Theories
- Trait Theories
-

5.2.2 Body Type Theory

The "Body Type" theory has its roots in ancient Greece philosophy, and allocates people into discrete categories of temperament based on physical or biological characteristics. This theory was popular in the Middle Ages, and still influences modern theories today. These theories, however, do not identify the *mechanism* of observed relationships between the body type and personality [Neill, 1999; Heineman, 1995].

The ancient Greeks proposed that there are four types or *humours* of people: Choleric, Melancholy, Sanguine and Phlegmatic. William Sheldon [1942] summarized that there are three basic body shapes (Ectomorph, Mesomorph, and Endomorph) with characteristic personality types. Tables in Appendix A summarize the body type, character and shape traits proposed by this theory.

5.2.3 Psychodynamic Theories

- Sigmund Freud
- Carl Jung
- Alfred Adler
- Karen Horney

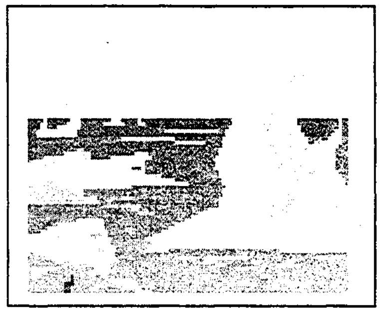


FIGURE 5.1: THE TIP OF THE ICEBERG

Sigmund Freund stipulated that the conscious (what we are aware of) and the preconscious (available memory) was just the "tip of the iceberg". The much larger mass below the water represents the unconscious (storehouse of impulses, wishes and inaccessible memories, memories and emotions associated with trauma). In contrast to the prevailing view of man as a rational being, Freud proposed that individuals are in a perpetual state of conflict motivated by a comprehensive realm of mental functioning unconscious and aggressive urges. Freud introduced the concepts of psychosexual stages, irrationality of behaviour and emotional motivators and their influences on personality and behaviour. He showed that behaviour was based on biology (ID) and he showed the impact of society (SUPEREGO) and the role of family dynamics in shaping personalities (tabulated in Appendix A) [Baldes, 2000; Boeree, 1997; Bull, 2000; Neill, 1999].

Other theories (behaviour, humanist) do not argue that the unconscious accounts for some of our behaviour, but rather how much and the extent of the influence.

Alfred Adler [Boeree, 1997; Bull, 2000; Neill, 1999] believed that social determinants influenced behaviour more than the unconscious impulses. He developed the theory of inferiority/superiority complexes: "The individual feels at home in life and feels his existence to be worthwhile just so far as he is useful to others and is overcoming feelings of inferiority". Adler hypothesized that inferiority complexes were caused by "inappropriate" parental behaviour. Karen Horney [Boeree, 1997; Bull, 2000; Neill, 1999] introduced theories that are more female-friendly. Carl Jung [Boeree, 1997; Bull, 2000; Neill, 1999] believed there were a number of underlying factors, which influenced the unconscious, including instincts, power and individualization (self-realization). He also argued that the ego can produce *harmony* in the mind as opposed to Freud's constant conflict, and that individuals have control over their future, while Freud believed prior causes shape our goals. Jung developed the idea of the collective unconscious (hypothesis that all people and cultures share some basic ideas) and archetypes (or mythic symbols). He also developed the idea of psychological types, e.g., sensing, intuiting, feeling, thinking, etc.

5.2.4 Humanism Theory

- Abraham Maslow
- Carl Rogers

The humanism theory places emphasis on personal freedom in making choices, individual worth, and potential for personal growth and self-fulfillment. This theory rejects the biological determinism or "body type" theory of personality, the irrational forces developed in the psychodynamic theory and the strict behaviourist theory (next section), which proposes that personality development is based on external stimuli [Boeree, 1997; Bull, 2000; Psychology Course Notes for HP603, 1999].

This approach is based on these concepts: individual subjective mental experiences (phenomenology) influence your behaviour and people control their behaviour. A person is more than the sum of their parts; therefore, personality must be considered through considering a whole person, not just a compilation of individual drives. Another key concept of the humanism theory is "self-actualization" or to become what you are capable of becoming. The individual chooses the direction of growth and the path taken (free will).

Abraham Maslow [Maslow et al, 1987] developed this theory where man carries out his own destiny using freedom of choice and the process of "becoming". Becoming as a concept implies that a person is never static and has a tendency toward fulfilling his/ her potential within the limits of heredity. Maslow's hierarchy of needs states that the needs at one level must be at least partially satisfied before those at the next level become important. Self-actualisation is only sought when all other needs are satisfied. The hierarchy of needs from top to bottom is shown in Appendix A.

Carl Rogers developed the "Self Theory" to understand personality. He put forward that there is a built-in motivation present in every life form to develop its potentials to the fullest extent possible. Rogers believed that all creatures strive to make the very best of their existence. Different elements of the "self" theory are shown in Appendix A.

5.2.5 Behavioural Theories

- Skinner

The strict behaviour theory states that your personality consists of the behaviours you show. Personality is learned through reinforcement or punishment of a particular response in a particular situation; hence, human behaviour is entirely determined by situations. A behaviour followed by a reinforcing stimulus results in an increased probability of that behaviour occurring in the future. This view allows for personality change through learning and showing different behaviours in different situations.

Skinner [1974] developed a systematic methodology of showing the influences of "operant conditioning". Skinner's definition of operant conditioning is: "the behaviour is followed by a consequence, and the nature of the consequence modifies the organisms tendency to repeat the behaviour in the future." Tests conducted with rats in cages (Skinner's boxes) showed the influences of reinforcing and aversive stimuli, schedules of reinforcement, and shaping behaviours [Baldes, 2000; Boeree, 1997; Bull, 2000]. Appendix A contains results for different applications of stimuli.

5.2.6 Social-Cognitive Theories

- Albert Bandura
- Julian Rotter
- Walter Mischel

The social-cognitive theory is an extension of the behaviour theory, as it proposes that learned behavioural patterns can occur through observation, not just through direct rewards or punishments. Personality is shaped by our cognitive constructs, which include goals, beliefs, expectations, values, etc. in addition to reward/punishment [Boeree, 1997; Bull, 2000; Psychology Course Notes for HP603, 1999]. This represents "social learning" as cognitive constructs are usually learned from other people. Cognitive constructs interact with the environment to influence behaviour patterns. This theory attempts to explain the processes of how behaviour is acquired, maintained, and changed.

Mischel's cognitive social learning theory placed emphasis on specific situational variables as being more important than personality traits in determining how people behave [Baldes, 2000; Psychology Course Notes for HP603, 1999]. He considered five broad "person variables" (as opposed to traits or dispositions) as central to study of personality, and these are shown in Appendix A.

5.2.7 Trait Theory

- Gordon Allport
- Raymond Cattell
- Hans Eysenck
- Costa and McCrae

The "Trait Theory" [Neill, 1999] is based on the supposition that there is a stable predisposition towards behaving in a certain manner. Clusters of surface traits reflect source traits, which underlie the basic aspects of personality.

Gordon Allport [Boeree, 1997; Neill, 1999] identified thousands of personality traits and grouped these into three categories: cardinal traits, central traits and secondary traits. A cardinal trait would be one trait that dominates personality across time and situations. It would be the most important component of a personality. Central traits consist of five to ten traits that are stable across time and situations. Central traits are the building blocks of personality. Most personality theories focus on describing or explaining central traits such as: honesty, friendliness or meanness, happiness, introverted or extroverted, and so forth. Secondary traits are characteristics that are only evident in some situations. Inconsistent traits reflect preferences, attitudes, and situational traits.

Raymond Cattell [Cattell et al, 1970] developed a personality factor model based on sixteen universal traits. He used advanced statistical analysis to develop the list of factors based on collected data. The bipolar list is listed in Appendix A.

Hans Eysenck [1972] developed a two-factor model consisting of "supertraits". Eysenck argued that a simpler two-factor model could encompass the 16 traits proposed by Cattell, as many factors were redundant. Eysenck argued that these traits were associated with biological differences; hence, the seat of personality function is in the central nervous system. One representation extended a combination of Eysenck's supertraits to explain the 'Greek humours', and is shown in Appendix A, along with another representation, which combines Cattell's model and Greek humours with Eysenck's [Neill, 1999].

Costa and McCrae [1985] have proposed a five-factor mode: OCEAN. The "Big Five" dimensions, each with six facets as shown below and further developed in Appendix A, are common across age groups and cultures. The stability of personality traits allows the prediction of motives, emotions, and interpersonal functioning [Baldes, 2000; Neill, 1999].

Big Five: OCEAN

- **O**pen: curious, broad interests, creative, original, imaginative, untraditional
- **C**onscientious: organized, reliable, hard-working, self-disciplined, honest, clean
- **E**xtravert: sociable, active, talkative, optimistic, fun-loving, affectionate
- **A**greeable: good-natured, trusting, helpful, forgiving, gullible, straightforward
- **N**eurotic: worries, nervous, emotional, insecure, inadequate, hypochondriac

There is no one unified theory of personality and behaviour. The above models reflect the different elements that serve as influences for personality and behaviour. The discussions typically questioned the effects of the various influences more so then refuting one theory in favour of another. The following illustration (Figure 5.2) graphically summarizes the interconnectivity of the above models [Boeree, 1997].

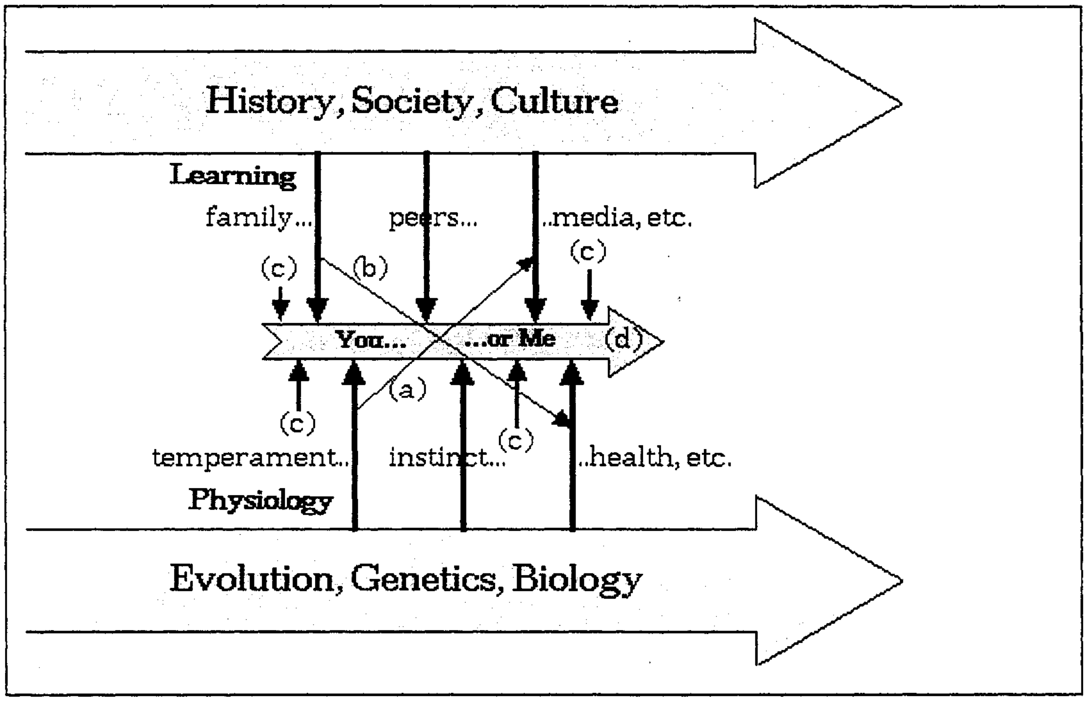


FIGURE 5.2: INFLUENCES ON PERSONALITY AND BEHAVIOUR [BOEREE, 1997]

5.3 Learning

The learning curve phenomenon was first reported in literature approximately seventy years ago. Simply stated: as the quantity of units manufactured doubles, the number of direct labour hours it takes to produce an individual unit decreases at a uniform rate. Yelle [1979] performed a survey of the learning curve literature, which is briefly summarized below.

The standard learning curve model follows the mathematical function

$$Y = KX^{n} \tag{5.1}$$

where Y is the number of direct labour hours required to produce the X^{th} unit.

K is the number of direct labour hours required to produce the first unit.

X is the cumulative unit number.

$$n = \frac{\log \Phi}{\log 2}, \text{ and is the learning index.}$$

Φ is the learning rate.

$1-\Phi$ is the progress ratio.

Since the initial description of a log-linear model does not apply to all situations, several alternatives have been proposed, and are illustrated in Figure 5.3. The common models are:

- The log-linear model.
- The plateau model.
- The Stanford-B model.
- The DeJong model.
- The S-model (i.e., cubic L-C).

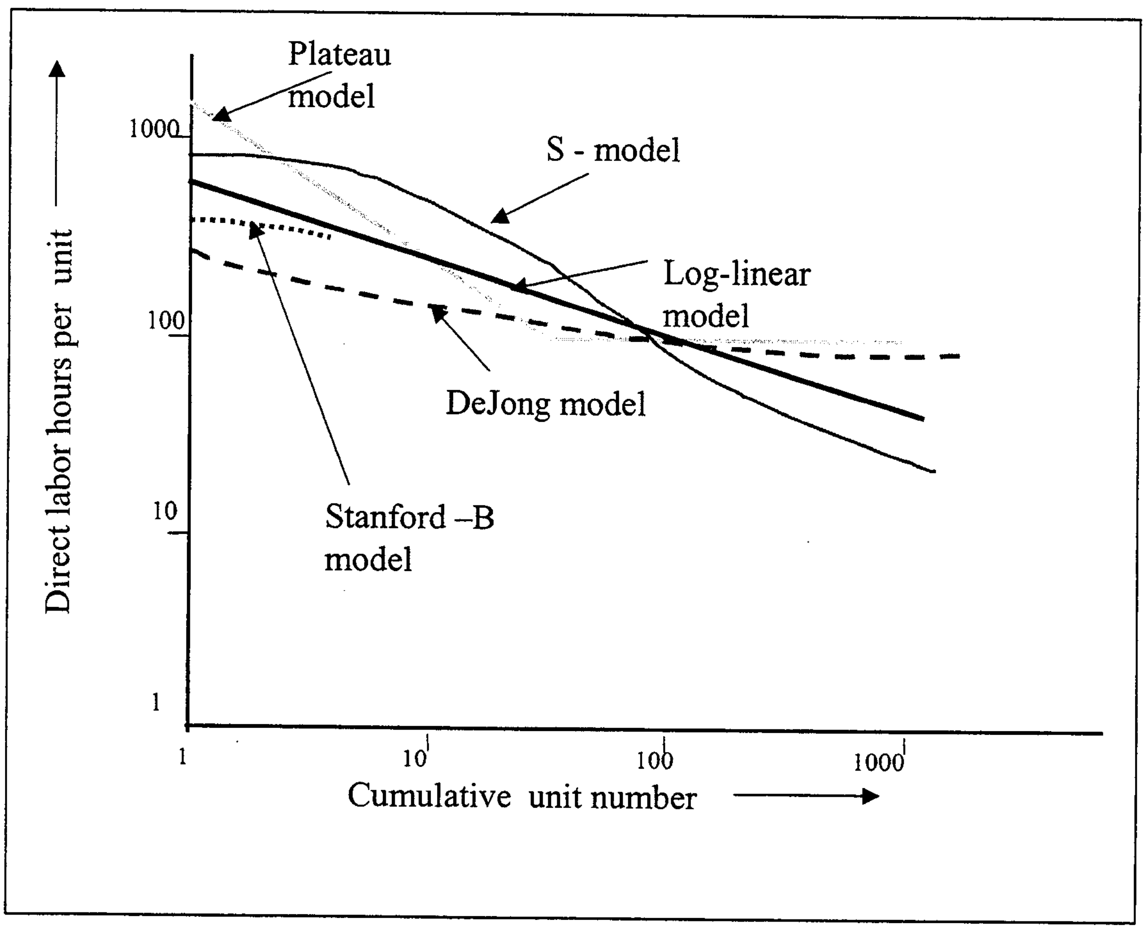


FIGURE 5.3: LEARNING CURVE MODELS [YELLE, 1979]

Workers who have experience or skills from prior jobs will require fewer cycles to reach a standard time. This concept is illustrated in Figure 5.4. The actual curves would obviously depend on the situation at hand. This phenomenon is used to aid setting labour standards and "launch curves" for a new model or product or process change. Another observable fact that occurs after a major product or process change: relearning.

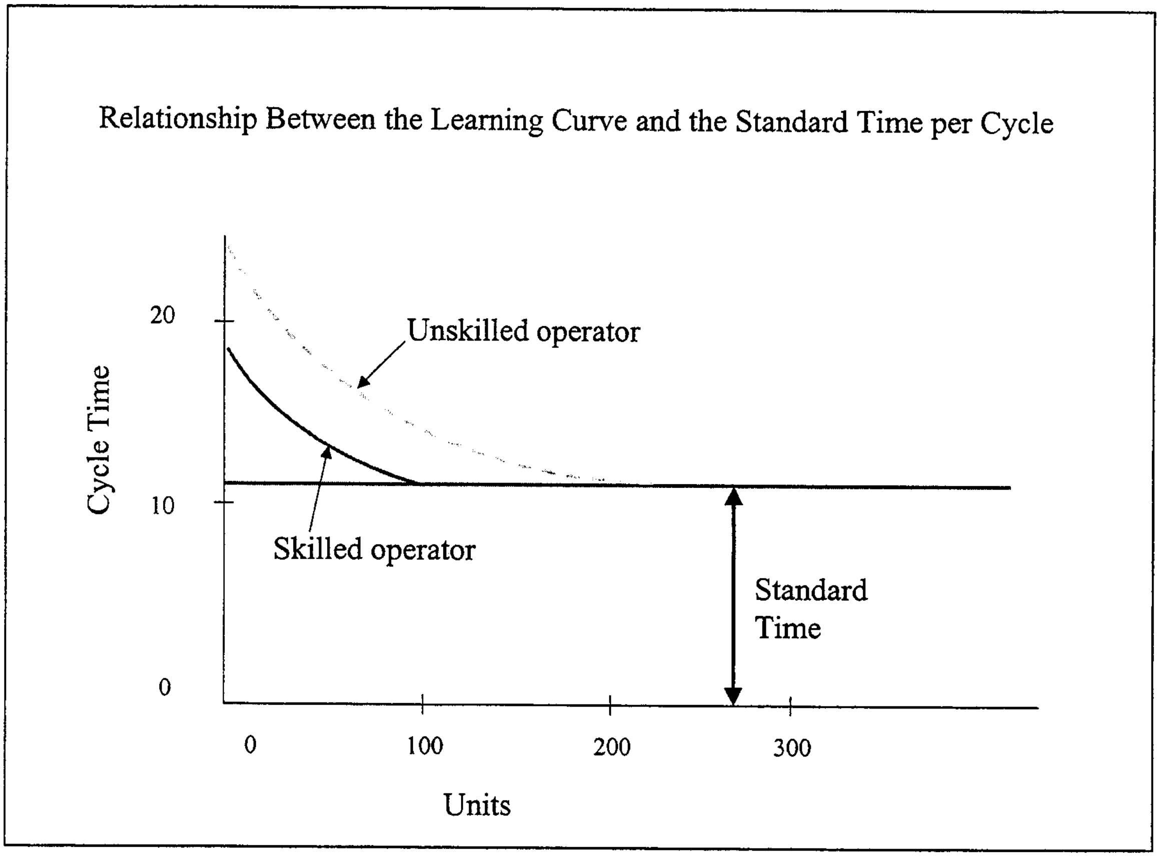


FIGURE 5.4: SKILLED VERSUS UNSKILLED LEARNING CURVES [YELLE, 1979]

Relearning occurs when there are interruptions or "learning discontinuities". As well as being launch related, this occurs when there is intermittent production of complex parts, or a worker being transferred to another previously held job, or a long period between training and application. Figure 5.5 illustrates a relearning scenario.

Yelle [1979] concludes that labour intensive operations have a much steeper learning curve slopes (higher progress ratio) than capital intensive operations. A plateau model is much more likely to occur in machine intensive manufacturing. The steady state condition in machine intensive manufacturing systems could be due to unwillingness to set new goals and invest more capital in order to introduce technological improvements necessary to reduce the labour hours. One finding linked technical knowledge and investment: approximately 85% of the changes in direct labour requirements were associated with changes in technical knowledge.

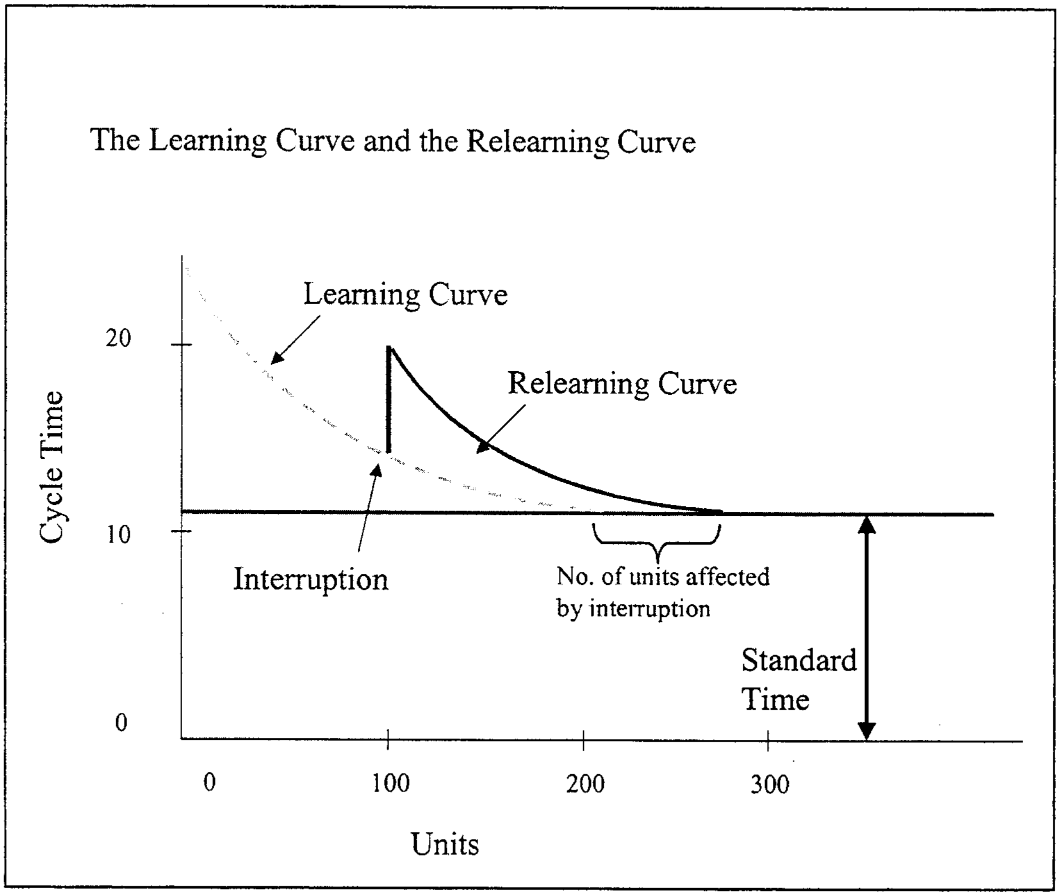


FIGURE 5.5: LEARNING VERSUS RELEARNING

The learning curve should be thought of an aggregate model (but not a cumulative function) as on a macroscopic level the learning curve represents labour learning as well as management and organizational learning. The larger the organizational effort, the flatter the learning curve (or the longer the adaptation to change) during the initial learning period [Yelle, 1979]. Learning is frequently described as a critical feature of the behaviour of an organization and learning capability is the only source of sustainable competitive advantage [Yin, 2001]. An organization that commits to learning and development at all levels (technical, managerial and manufacturing sectors) and has the ability to adapt to changes is a ''learning organization''. Yin [2001] performed an empirical study relating organizational learning capability to the performance of Computer Integrated Manufacturing (CIM) firms or plants. He concluded that learning capability plays a significant role, and the learning must be aligned properly to generate effective performance. Performing research and development (R and D), and learning to use the sophisticated manufacturing and information tools were effective in improving the flexibility, responsiveness and performance of the Computer Aided Design and Computer Aided Engineering (CAD/CAE), Computer Aided Manufacturing (CAM) and Material Resource Planning (MRP) tools. The study highlighted that management's learning was the most dominant factor in achieving the required objectives. As most decision-making issues and many operating problems are dynamic, unstructured and qualitative, effective solutions to those problems depend on learning within the management teams.

Gibson and Plaut [1995] develop a dynamic model based on an application of control theory to study human learning performance. This model was developed to determine how to facilitate learning in dynamic decision making tasks. Their approach divided the task into two interdependent sub problems: (1) learning how actions affect the environment, and (2) learning what actions to take to achieve certain goals. The model was compared to human performance, and generated results that if smoothed had a log-linear format. There was much noise in the data, which is to be expected based on the model's dynamic nature.

The above models focus on the fact that manufacturing knowledge is usually measured using a "learning by doing" approach. Learning by doing is a process that occurs after an innovation has been transferred to workers [Ahanotu, 1998]. An effective learning cycle consists of plan, act, reflect, change, and plan again. Typically production workers are limited to the "act" part of the learning cycle. Ahanotu astutely points out that if production workers are not part of the exploration or planning process for new product or process innovations, they are resistant to the resultant changes. Establishing an infrastructure that fosters continuous learning and innovation positively contributes to the performance of the manufacturing firm while creating empowered production workers.

5.4 Fatigue

Work related fatigue has been studied and empirical models generated [Fletcher and Dawson, 2001] but there is no classic fatigue model in the literature. Work related fatigue due to shift work, overtime, and the external environment affects safety, productivity and efficiency and has been studied extensively in the US military and the trucking industry. Dondeti and Mohanty [1998] use the concept of work content to define a fatigue model for n independent jobs available for processing on a single machine. This model can be extended to alternative environments.

Let q_j denote the units of the work content of each job ($j=1, 2, \ldots, n$). *Let* $F(u)$ denote the cumulative time required to process a total of u units and let $f(u)$ be the corresponding rate of change in the cumulative time function $F(u)$. When processing a total of u work units, it will require the amount of time equal to $f(u)du$ to produce du units of work.

Therefore:

$$F(u) = \int f(u)du \tag{5.2}$$

where $F(0) = 0$.

If the processing time is constant, then $f(u) = f_0$; hence, the processing time $p_j = f_0 q_j$, where $j = 1, 2, \ldots, n$.

This assumes that when the fatigue function $f(u)$ varies with u, it is a positive, continuous and monotonically increasing function of u. Consequently, the processing time and the amount of defects are both functions of work content as well as prior work. Figure 5.6 represents a straight line, convex and concave fatigue curve.

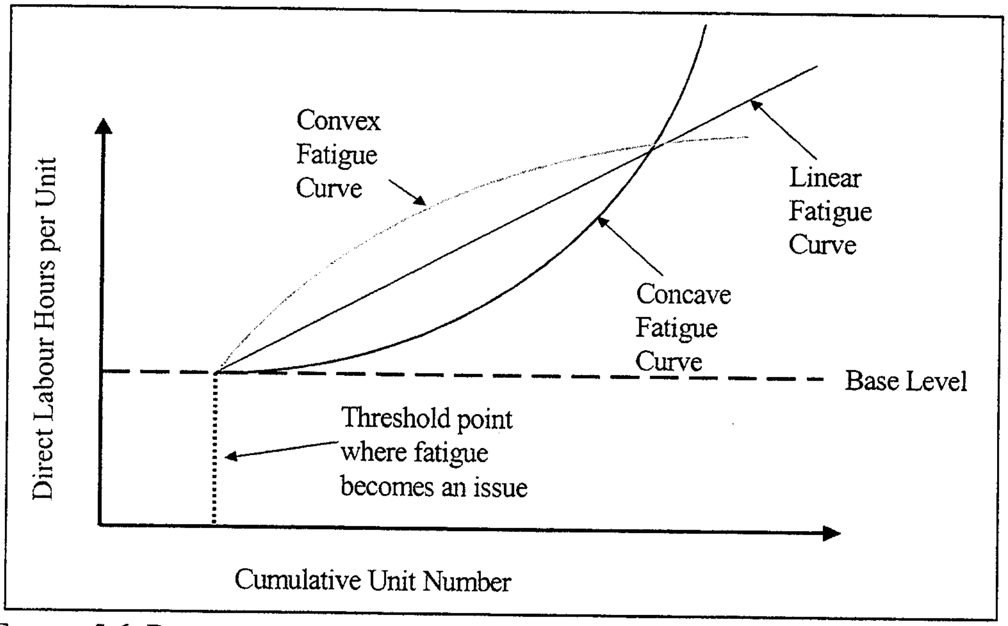
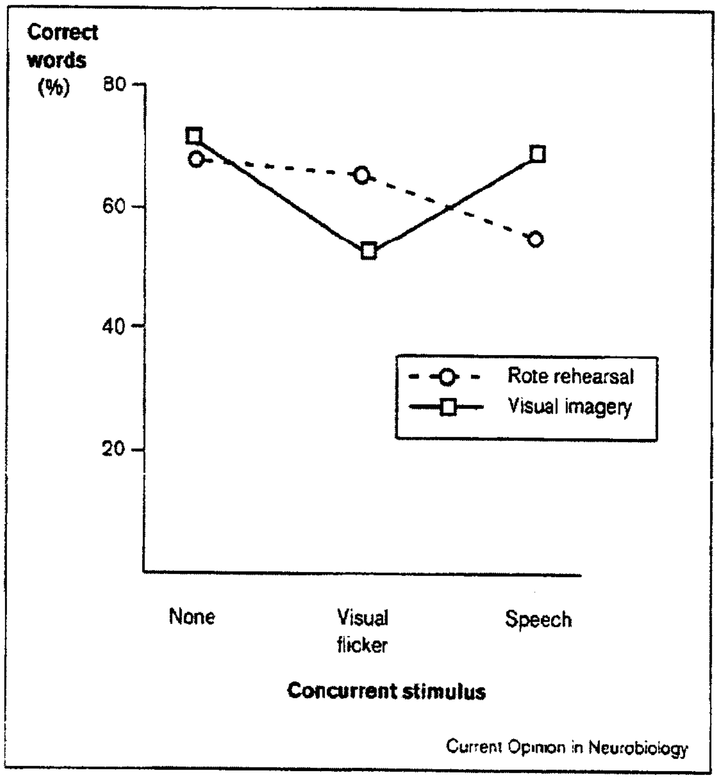


FIGURE 5.6: RELATIONSHIP OF FATIGUE ON DIRECT LABOUR HOURS

5.5 Memory

Most models of the human mind distinguish between different types of memory: modality specific sensory registers (in which auditory and visual stimuli are represented for no more than a few seconds), short-term or working memory and long-term memory. It is generally accepted that memory consists of the three aforementioned information storage modes and a set of processes which acts upon the information storage. The three main general processes are encoding, maintenance and retrieval. Different theories specify different properties for the memory storage mode and processes. The "Magic 7" described by Miller [1956] is almost universally accepted as the maximum capacity limit for short-term memory. Miller's paper dealt with "immediate" memory, as at that time period most scientists believed that there was only one human memory system. Later, the idea of a separate "short-term memory" system was defined along with short-term memory's characteristics, uses and limitations.

Along with the short-term memory having a limited storage capacity (seven, plus or minus two items or "chunks"), it also decays or becomes distorted. Short-term memory becomes inaccessible after a relatively brief interval (estimates range from 12 to 30 seconds). Distortion or interference may occur when new information displaces older information. This could produce memory retrieval errors in which one recalls information that is similar to but not identical with that which is needed. Not all information is retained equally. The last items on a list are generally recalled more accurately than the first items on a list. Active rehearsal (repetition) improves memory, whereas information is lost during interruptions [Baddeley, 1998]. Figure 5.7 shows the experimental results of the effects of interruptions (distractions) on working memory.



Evidence for separate visual and verbal coding in memory. Subjects attempted to learn a list of words using either visual imagery or rote verbal repetition, while trying to ignore either a flickering visual pattern or background speech. When subjects used imagery, only the flickering light impaired performance; when they used rote repetition, the opposite pattern was found

FIGURE 5.7: EFFECTS OF INTERRUPTIONS ON WORKING MEMORY [BADDELEY, 1998].

"Chunks" of information are composite units created by grouping or organizing separate elements based on rules stored in long-term memory. Short-term or working memory is used to temporarily hold and manipulate new information or information retrieved from long-term memory. The preferred term for short-term memory is "working memory", as it demands attention. Baddeley [1998] has proposed two independent sub-processors for working memory: one that manipulates and stores visual-spatial images, and one that manipulates and stores auditory information, shown in Figure 5.8.

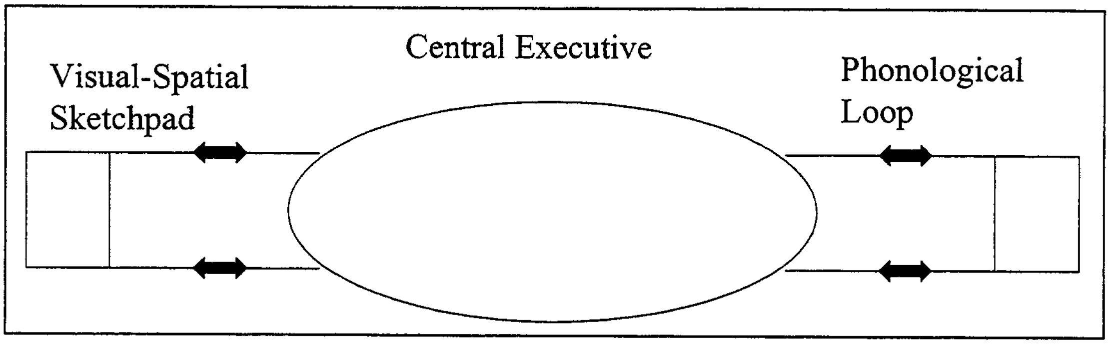


FIGURE 5.8: WORKING MEMORY MODEL [BADDELEY, 1998].

Long-term memory can store a very large quantity of information and can maintain that information for very long periods of time. The mechanisms, which organize information in short-term memory and convert it into long-term memory and the retrieval mechanisms depend on many factors, which are being researched today.

The cognitive ergonomics implications of the working memory limits [Wickens et al, 1998] drive several design recommendations including:

- Minimize the working memory load - reduce the number of items and the time it takes to rehearse those items in working memory.
- Provide visual material – this allows for referral at a later stage.
- Exploit "chunking" – represent information in simple, meaningful units
- Minimize confusion through exploiting different working memory codes – represent similar information using different modalities

Also from Wickens et al [1998], to assist long-term memory processes:

- Encourage regular use of information
- Standardise to reduce the number of competing mental conceptualisations of the same process.
- Use memory aids – this is particularly important for infrequently performed tasks
- Design information so that it will be remembered.

5.6 Environment

There are several other factors that influence human performance. The physical environment (noise, fumes, illumination, climate and temperature), the diversity and complexity of the tasks associated with the processes or products, the skill level of the individuals and the working team, the skill set of the team and the culture of the environment all influence an individual's behaviour.

Gollop and Monahan [1991] proposed a diversification index based on the Herfindahl-Hirschman Index (HHI) as a statistical test of the heterogeneity in a production-based grouping. The HHI was originally defined as the sum of the squares of the shares of all sellers in the relevant market and has been used in economic studies, such as an indicator of monopoly power. The product diversification index here (PDI) for the j^{th} product is defined as:

$$PDI_j = 1 - \sum_{j=1}^{J} w_j^2 \tag{5.3}$$

where w_j is the percentage of the j^{th} dissimilar product (option) in total production

This in turn needs to be combined with a complexity index. Complexity increases with:

- number and of features to be manufactured and tested,
- diversity of features,

- number of tasks,
- type of tasks, and
- effort to generate tasks.

From Cooper et al [1992] product complexity is measured as the volume weighted average as defined below:

$$CI_j = c_j * x_j \Big/ \sum x_j \tag{5.4}$$

where c_j is the complexity value for product j, and x_j is the volume of product j.

Reuer et al [2002+] investigate novelty and heterogeneity with respect to skills and culture to determine their influences on performance for international joint ventures. They characterized each industry's skill requirements in order to calculate these measures. Skill novelty was defined as the average distance between the focal transaction f and the joint ventures in the firm's experience set or the difference between needed skills and actual skills. Skill heterogeneity is the measure of diversity of the firm's previous experience.

$$Skill\_Novely = \frac{1}{N} \bullet \sum_{j=1}^{N} [\sum_{i=1}^{I} \sqrt{\frac{(P_{ij} - P_{if})^2}{s_i^2}}] \tag{5.5}$$

where N is the number of joint ventures in the firm's experience base

I is the number of occupational divisions

P_{ij} is the percentage of employees in occupational division i for joint venture j's industry

P_{if} is the percentage of employees in occupational division i for the focal joint venture f

s_i^2 is the sample variance of employment percentages in occupational division i across all industries, which is used as a weighting factor.

$$Skill\_Heterogeneity = \sqrt{[\frac{1}{I}\sum_{i=1}^{I}\frac{v_i^2}{s_i^2}]} \tag{5.6}$$

where I is the number of occupational divisions

v_j is the sample variance in employment in occupational division i across the industries in which the firm has joint venture experience (i.e., $j \in J$).

P_{if} is the percentage of employees in occupational division i for the focal joint venture f

s_i^2 is the sample variance of employment percentages in occupational division i across all industries, which is used as a weighting factor.

Analogous measures for cultural novelty and heterogeneity were calculated based on the geographic locations of the firm's prior experiences with joint ventures. The scales that Reuer et al used to define the "characteristics of a culture" were based on uncertainty avoidance, individuality, tolerance of power, and masculinity.

$$Cultural\_Novely = \frac{1}{N} \bullet \sum_{j=1}^{N}[\sum_{i=1}^{I}\sqrt{\frac{(C_{ij} - C_{if})^2}{s_i^2}}] \tag{5.7}$$

where N is the number of joint ventures in the firm's experience base

I is the number of scales being used to define culture

C_{ij} is the score for scale i for the host country joint venture j

C_{fj} is the score for scale i for the host country of the focal joint venture j

C_{if} is the percentage of employees in occupational division i for the focal joint venture f

s_i^2 is the sample variance of scale i

$$Cultural\_Heterogeneity = \sqrt{[\frac{1}{I}\sum_{i=1}^{I}\frac{v_i^2}{s_i^2}]} \tag{5.8}$$

where I is the number of scales being used to define culture

v_j is the sample variance in scores for the i across the host countries in which the firm has invested in joint ventures

s_i^2 is the sample variance of scale i across all countries

5.7 Summary and Conclusions

No one of the above theories completely describes personality and behaviour, fatigue and memory – a distinct challenge when attempting to model performance. Heredity and environment affect all these human characteristics. The 'unconscious' influences our behaviour – this is the equivalent of a random element in a system model. The concept of free will is a fundamental tenet of our society. We wish to improve ourselves such that we attend our goals. This complements the behavioural theory: positive and negative stimuli to an action (feedback) affect our actions, whether being applied directly or through observation. Thus we learn and acquire knowledge, and tailor our behaviour and performance accordingly. In similar situations, we draw on our experience (memories) into order to address the new situation. Interruptions and fatigue negatively affect both our physical and cognitive capabilities.

The trait theory serves as the foundation for many popular personality tests (Myers-Briggs), which are used in management training and team building exercises today. However, in itself the trait theory cannot be used for a system model but factors from the trait theory can be extended to influence the cultural indices. The environmental indices (product diversity, complexity, skill and culture novelty and heterogeneity) can be modified to fit alternative environments, and serve as a basis for influencing learning, memory and fatigue parameters. Figure 5.9 illustrates the human performance model.

The intangible human performance variables are complex, interdependent and not well understood. The traditional manufacturing strategy of dedicated, specialized equipment and the push manufacturing philosophy effectively detuned human psychological and cognitive influences. Tasks were simplified, and work in process buffers absorbed any human related variations as well as any process related variations. Although cost effective, the inertia in the system is immense. Changes are resisted because it directly influences the process stability. However, today's environment is volatile: responsive adaptation without compromising costs, quality and selection is the new manufacturing paradigm. Today's manufacturing models consist of complex physical configurations. Those that consider man-machine integration must also include some provision for the intangible human factors discussed in this chapter, as the success of the enterprise is very dependent on the employees' behaviour, knowledge acquisition, skill sets, and level of motivation.

This adds another level of complexity, but understanding the human parameters influences the design criteria. This directly affects the system usability and is relevant to the process output, as shown by the human performance models presented in the next chapter. (However, it must be noted that bulk of the work has been done with human performance models is in the specific field of human-computer interactions.)

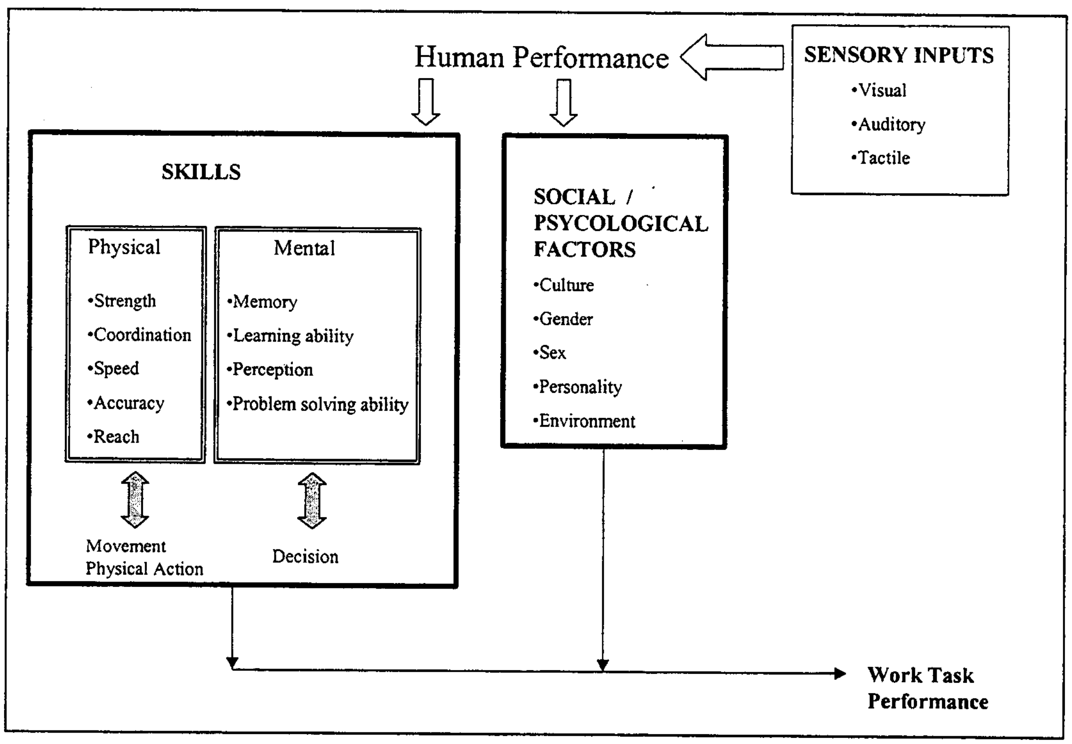


FIGURE 5.9: HUMAN PERFORMANCE MODEL

6.0 HUMAN PERFORMANCE MODELS

6.1 Introduction

Humans have the widest range of physical and mental skill sets and dexterity of any creature. But humans are not "general purpose devices" capable of performing any and every task with equal skill and proficiency. Proficiency in any endeavour is obtained incrementally; skills are acquired by gradually increasing the complexity of the sub tasks, either physical or cognitive.

A broad spectrum of diverse disciplines has presented theories, perspectives and insights with respect to human performance models. This includes, but is not limited to: psychology, sociology, engineering, computer science, biomechanics, and medicine. Human performance models focus on limited aspects of human performance such as models for personality, learning, social behaviour, cognitive skills, motor skills, and man-machine systems. The particular models of interest for this research are those that combine human performance with system performance. In a man-machine environment, these models are used in system design, development and evaluation for military, air traffic control, process control and manufacturing applications [Grant, 1990]. The common thread for the above applications consists of the challenge to model performance in a dynamic, multi-tasking environment, as:

- tasks may overlap in time,
- there are conflicting demands,
- there are disparate activities and constant interruptions,
- there are variations of the task complexity, and
- there are multiple human / machine interdependencies and interactions.

Human performance models may be designed to predict the outcome based on various inputs, or can describe performance results from existing data, as in the various models of the learning curve described in chapter five. Models can focus on the underlying mechanisms by which output is generated, or the actual output. Simple models focus on single tasks, such as the necessary movements required to perform an activity. Complex models try to address multitasking and its inherent complexities at the individual, team and system levels.

In modern society, people are utilizing tools with increasingly complex technology. In almost every environment, the expectations are increased performance with reduced costs. The human performance models are necessary to design systems that balance human needs and capabilities i.e., the physical system is designed around the people within the environment to augment the results of both the human and machine elements. With respect to the "man-machine" environment, this section presents an overview of human performance models in three broad categories: "physical" human performance models, "cognitive" human performance models, and human performance models using the "systems" approach.

6.2 "Physical" Human Performance Models

"Physical" human performance models consist of physiological and biodynamic models, which focus human physical characteristics such as physiological dimensions, capabilities and limitations. This leads into several areas of study, such as:

- Anthropometrics, which is the study of human body measurements;
- Biomechanics, which is the study of mechanical operation (motion and forces) of the human body; and
- Ergonomics, which is the study of work ("Latin: ergon = work, nomic = the study of").

6.2.1 Anthropometrics

Anthropometrics entails the systematic collection and statistical correlation of measurements of the human body. This data can be used to describe the "user" or "target" population for a particular product or the workspace envelope needed by personnel to perform their tasks. Designers can specify in advance what proportion of a population they want their design to satisfy by using the appropriate percentile dimensions within their design. Many designers use the 5^{th} and 95^{th} percentiles to define the range which they accommodate within their design. This ensures that the dimensions will suit 90% of the population. More stringent guidelines may be required in the military or public sectors; therefore, the design range may consist of the 3rd to the 97th percentiles [Defence Standard 00-25 (UK), 1991]. Static (or structural) dimensions are taken with the subjects (a representative population) in a rigid, standardized position.

Static dimensions do not account for joint flexibility and movement; hence, dynamic (or functional) dimensions are measured in "working positions". In this context, "dynamic" refers to changes of the physical body position in space, not time. These spatial measurements take into account of certain degrees of body movement and flexibility. This is illustrated in Figure 6.1 [Defence Standard 00-25 (UK), 1991].

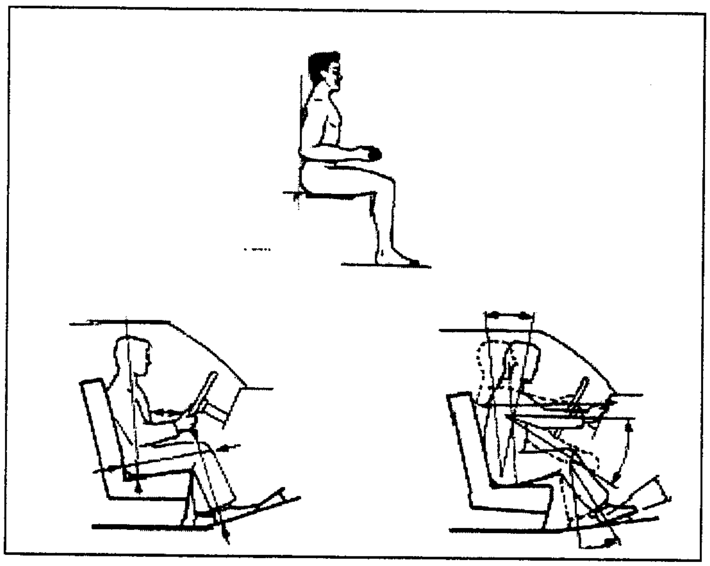
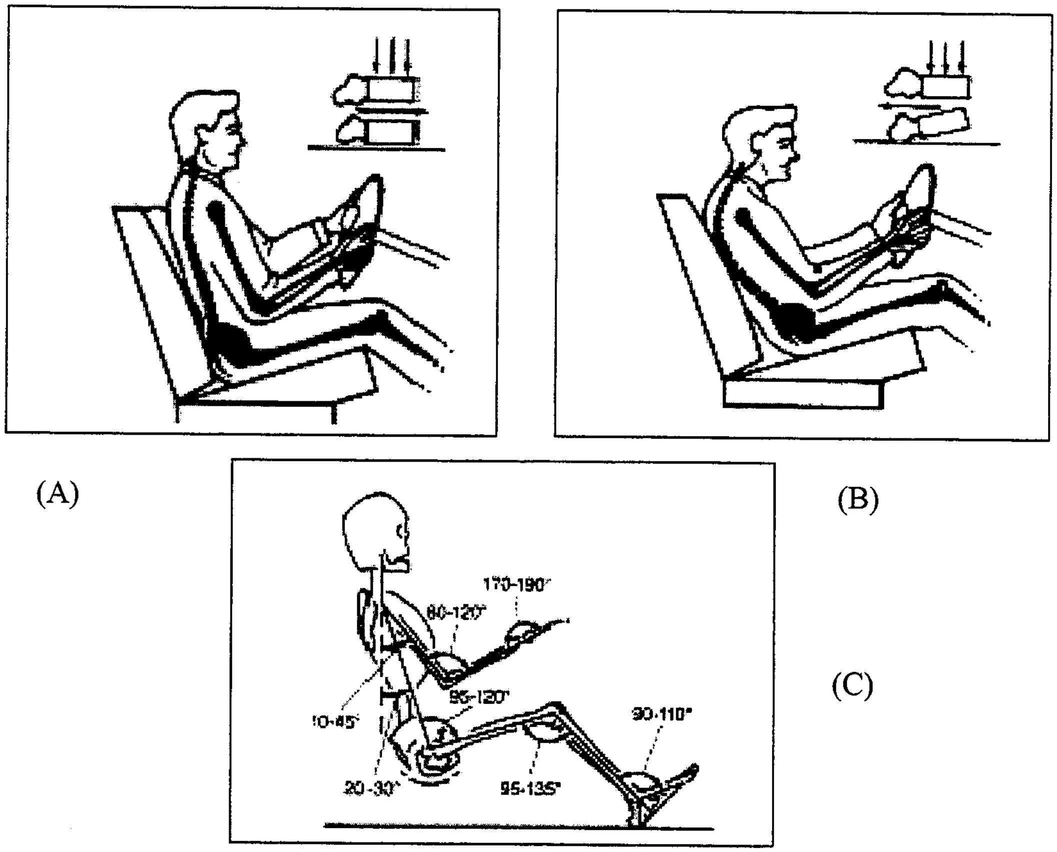


FIGURE 6.1: DYNAMIC ANTHROPOMETRICAL DATA [DEFENCE STANDARD 00-25 (UK), 1991]

It must be emphasized that individual body members do not operate independently. A simple example from the Defence Standard 00-25 (UK) [1991] illustrates this point: the practical limit of arm reach is a function of arm length, shoulder movement, partial trunk rotation, and the possible bending of the back.

Consequently, all spatial and dimensional problems cannot be resolved on the basis of structural or static body dimensions. As well, there are several dynamic dimensional alternations due to the many degrees of freedom within the human body. This not only effects how a task is performed or a product is used, but also introduces factors such as stooping, slouching, twisting, and so forth (Figure 6.2).



Adequate back support is required for seating including automobile driver seats. Figures A and B illustrate desirable and undesirable postures in relation to the spine. With unsatisfactory support (shown in figure B) and angles between the vertebrae (*shown in the inset*) can generate discomfort and conceivably cause spinal complications. The angles of the various body joints shown in figure C are considered to be desirable in items of anthropometrical considerations.

FIGURE 6.2: AUTOMOBILE DRIVER'S SEAT [DEFENCE STANDARD 00-25 (UK), 1991]

6.2.2 Biomechanics

Biomechanics is the study of the mechanical operation of muscular activity applied to biology. Within the human body much research has been performed in the areas locomotion and exercise. Kinetics, kinematics, and inverse dynamics are applied to muscle and joint actions and functions. From Richards [1999], kinetics is the study of forces, moments, mass and acceleration without any detailed knowledge of the position and orientation of the body. Conversely, kinematics describes the effects of the forces on the system (which is movement - displacement, velocity and acceleration) without reference to the forces involved. Inverse dynamics combines the study of kinetics and kinematics. This may be used to calculate forces and moments about the joints. Work, energy and power during movements may also be found if the physical model joint positions and muscle attachments are properly defined.

There are three basic building blocks for a model: the bones, the bone linkages (joints) and the muscles. The problem defining and developing a human performance model follows. Muscles are only capable of contracting; hence more than one muscle is necessary to control position for one degree of freedom of a joint. There two types of muscular contractions: "isometric and "isotonic" contractions. With isometric contractions, the muscle length is fixed and the tension load varies, while with isotonic contractions the muscle tension is constant and the muscle length shortens. Each muscle consists of several "motor units". Muscle force is a sum of several factors: muscle length, cross sectional area, contraction speed, fatigue, muscle fibre and the motor unit firing rates. In addition to the complexity of the muscular structures, several joints have multiple degrees of freedom. Joints are not always perpendicular, coplanar or intersecting, i.e. the elbow flexion and pronation axes or there are joint interdependencies i.e. the scapula. In essence, biomechanical human performance models are non-linear, interdependent, multiple degree of freedom linkage systems with multiple constraints whose performance will vary over time.

6.2.3 Ergonomics

Ergonomics - or human factors - is a body of knowledge about human physical and psychological characteristics, human limitations, and other characteristics that are relevant to design. This information is applied to design tools, machines, systems, work environments and tasks for effective human use. Inherent is the safety and comfort of the worker to increase the productivity and quality of the end product or service.

Factors that are considered in work task designs are:

- the body positions (velocities, accelerations) throughout the work task,
- the forces or pressures on the controls or tools,
- the compressive low back disk forces when lifting ,
- the cardiovascular response when performing heavy labour,
- the location, form and size of the tools, controls, and displays for the man-machine interface,
- the amount of task repetitions,
- the task duration, and
- external environmental variables such as vibration, temperature, and so forth.

Modern ergonomic human performance models build upon anthropometrical data and biomechanical theory and models.

F. W. Taylor was a pioneer of "Scientific Management", and was primarily concerned with finding the best method of doing work. Other pioneers are Frank and Lillian Gilbreths who focused on the motion study analysis of industrial tasks. They established the principles of motion economy and introduced concepts such as time motion analysis, standardized tools, methods, materials and tasks. These methodologies serve as the basis for industrial ergonomics today. Ergonomic analysis of man-machine systems does not exclusively focus on optimizing worker efficiency through elimination of redundant movements; the importance of ergonomics is focusing on designing the "best fit" between human capabilities, abilities and limitations and the machine interface [Kothiyal, 2000].

As military equipment has become more sophisticated (airplanes, submarines, etc.), the military has great interest in man-machine interfaces, and are continuing to develop increasing complex and sophisticated human performance models [Defence Standard 00-25

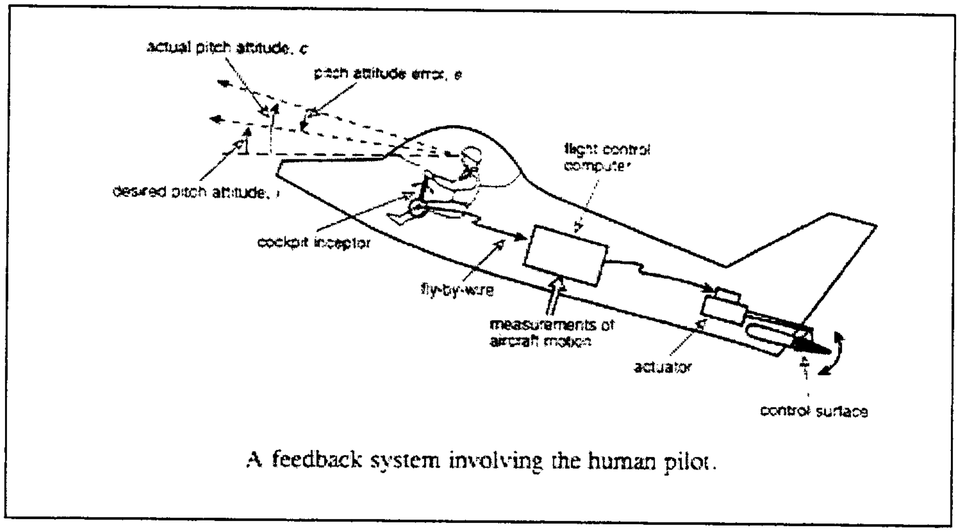
(UK), 1991]. The models have expanded into real-time predictive models, and are discussed in the next section.

6.2.3 Control Theory Models

The modelling of dynamic human performance has been developed using control theory, extending the physical models from the spatial domain into the time domain. Mathematical models of human *response* range from simple, manual tracking tasks to complex, multivariable controls problems. Sub-models include perceptual, cognitive and motor activities, which lead to complex, dynamic interactions. The human operator is modelled as an information processing unit or a control/decision element in a closed loop system [Baron et al, 1990; NRC Committee for Flight Safety, 1997] with sensory inputs and motor outputs. It is also assumed that the operators within the model are qualified, proficient, experienced experts, hence the operator's performance approximates the optimal qualities of an inanimate system performing the same function, but with "human" limitations or constraints with respect to the sensory inputs and response [Baron et al, 1990; NRC Committee for Flight Safety, 1997]. This type of modelling methodology is not appropriate for discrete tasks. These human performance models focus on the man-machine system's overall effectiveness with respect to accuracy of control, stability, responsiveness, and the ability to compensate for disturbances, [Doman and Anderson, 2000; Batavia, 1999; Davidson and Schmidt, 1994, 1992; Baron et al, 1990; NRC Committee for Flight Safety, 1997] and have been used to develop sophisticated airplane and automobile control models.

6.2.3.1 Pilot-Vehicle Systems

Pilot-vehicle systems simulation and analysis provide a basis for sensible, stable aircraft design. The human performance model simulations provide data and insight into understanding, avoiding and correcting aircraft-pilot coupling problems such as pilot induced oscillations [NRC Committee for Flight Safety, 1997]. Human performance models for a pilot-aircraft system (Figure 6.3) have developed from two broad categories: (1) using the classical single-input single-output closed loop feedback system, as shown in Figure 6.4, and (2) models using a multivariable philosophy.



A feedback system involving the human pilot.

FIGURE 6.3: A FEEDBACK SYSTEM INVOLVING THE HUMAN PILOT [NRC COMMITTEE FOR FLIGHT SAFETY, 1997]

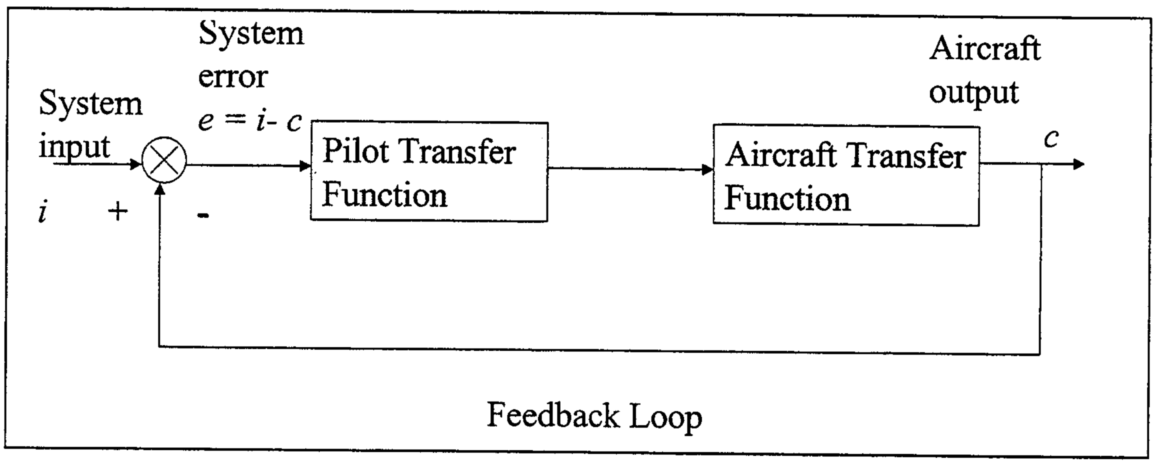


FIGURE 6.4: A CLOSED LOOP PILOT-VEHICLE SYSTEM [NRC COMMITTEE FOR FLIGHT SAFETY, 1997]

The optimal control model (OCM) introduced by Kleinman, Baron and Levison [Baron et al, 1990; Committee, 1997; Davidson and Schmidt, 1994; Doman and Anderson, 2000] is the fundamental multivariable "attention-sharing" model used in modelling human performance, and is illustrated in Figure 6.5.

This model assumes that the control strategy (or the amount of compensation) implemented by the pilot changes over time, and that the control strategy is subject to human limitations, i.e. decisions are based upon incomplete, noisy, and delayed information (the visual-cognition time lag) [Baron et al, 1990; Committee, 1997; Davidson and Schmidt, 1994; Doman and Anderson, 2000]. The degree of uncertainty or noise with respect to the state is based on the type and quality of the available information, the pilot workload, the task at hand, and the environment (visibility, turbulence, night time flights, and so forth). A Kalman filter state estimator and a state prediction model (such as the least-mean-square methodology) simulate the operator's behaviour or performance in real time. Consequently, the model is dynamically updated based upon the changing environment: in essence the human performance model adapts or "learns" in real time.

The basic OCM model has undergone several refinements [Doman and Anderson, 2000; Davidson and Schmidt, 1994; Davidson and Schmidt, 1992]. For example, Davidson and Schmidt [1992] developed the modified optimal control model (MOCM), which compared more favourably with measured results by modifying the simple time delay with a more sophisticated transfer function, as shown in Figure 6.6.

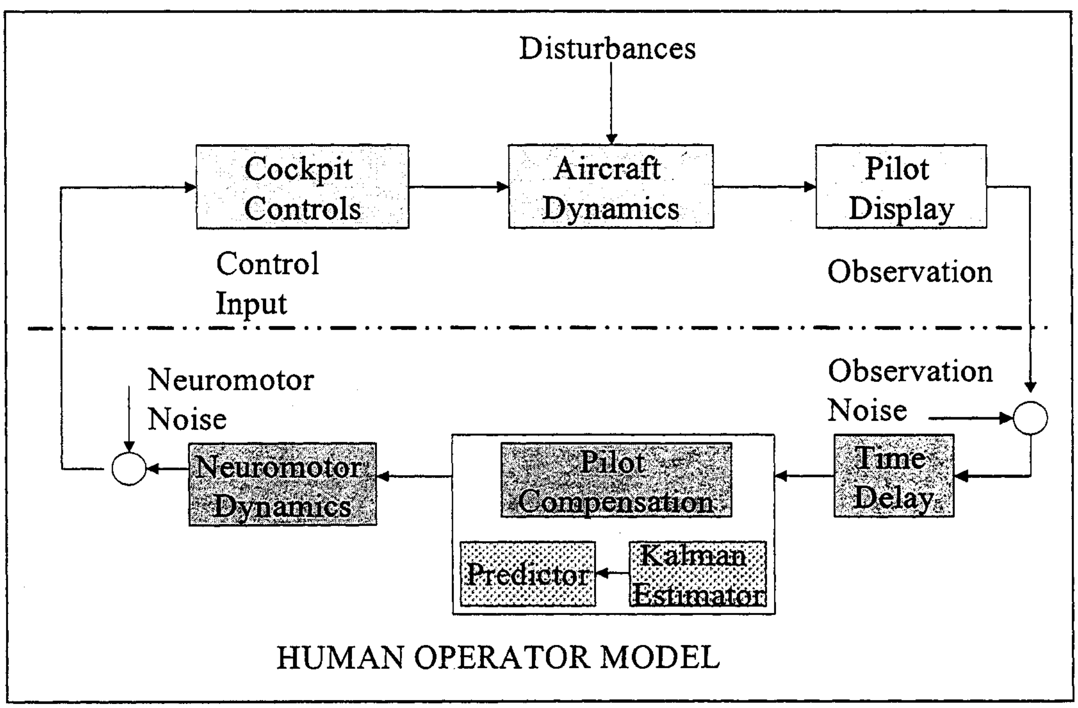


FIGURE 6.5: OCM HUMAN OPERATOR MODEL [NRC COMMITTEE FOR FLIGHT SAFETY, 1997]

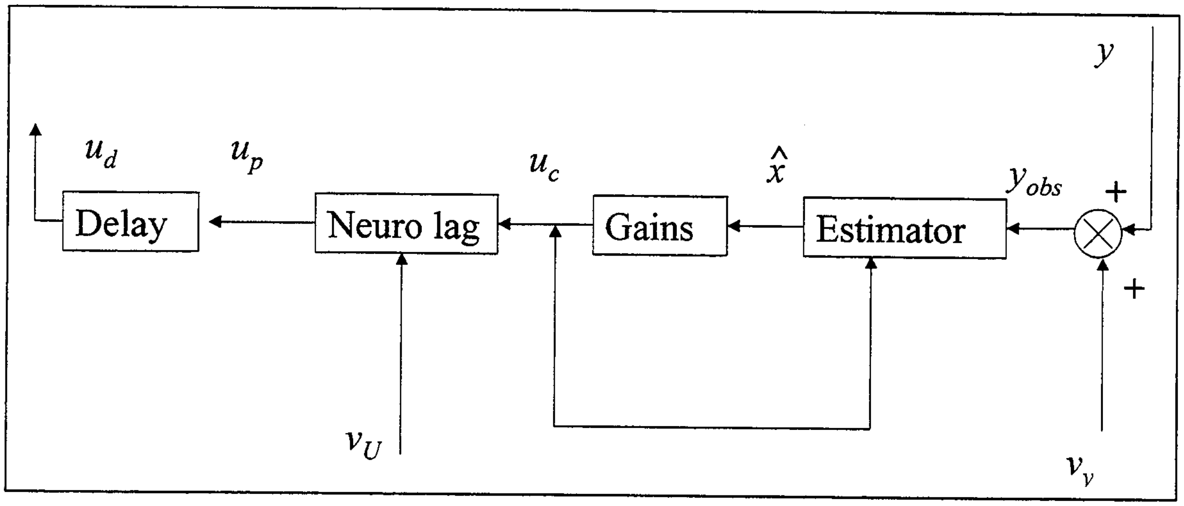


FIGURE 6.6: MODIFIED OPTIMAL CONTROL MODEL [DAVIDSON AND SCHMIDT, 1992]

6.2.3.2 Driver-Automobile Systems

The control theory models for driver-automobile systems are similar to those developed for pilot-aircraft human performance models. There are four major sub-systems within the driver-automobile system: the driver's perception or situational awareness, speed and path decisions, speed control and path control [FHWA, 1996]. From Batavia [1999], initially drivers where modelled as a gain and a time delay and the vehicle's lateral position was modelled as an integration of the steering wheel angle. This simple model has been expanded upon to take into account perceptual input data such as roadway characteristics and the vehicle state (past lateral displacement, future roadway curvature, and the driver vantage point) as research has shown that information on the upcoming road curvature eliminates the some of the effects of perceptual and reaction lag (the decision and control modules). Other driver models included a multiple level models that combined "precognitive" open loop controls for the trajectory of the driver with closed loop controls for vehicle performance and road information. As well, some models incorporated a non-linear hysteresis element that was introduced to model the driver oscillations while driving on straight roads. The main assumption in these control theory approaches to human performance modelling is that the driver- automobile man-machine system can be simulated using 2nd order systems [Batavia, 1999]. Stochastic and non-linear effects cannot be modelled well using these approaches.

6.2.4 Physical Model Summary

Although these ergonomic and control theory models address how people interact with machinery and how to design the work envelop and controls for machines and vehicles, these models do not apply to computer systems. These models are based on tools, equipment and machinery that cannot be programmed (i.e., remain static throughout usage). A more complete human-system performance model addresses the interactions and issues of all the elements within a system, which includes human-computer interactions. Human Computer Interaction (HCI) theories combine the fields of software engineering, ergonomics, sociology, artificial intelligence and cognitive psychology to create a model to predict human performance that includes "mental work" [Blackwell, 1999; Grant, 1990; Griffith, 2002; Neerincx, 1995; Nunes, 2001]. Cognitive psychology deals with how humans perceive their surroundings, and how humans react, think and plan. This area of research is not as mathematical or as precise as the physical performance models. A brief overview of human computer performance models is presented in the next section.

6.3 "Cognitive" Human Performance Models

6.3.1 Introduction

There are several alternative theories to predict human performance in the field of Human Computer Interactions (HCI). The models have a generic architecture – visual input, physical output, memory and a problem-solving processor (Figure 6.7). Performance is measured for the amount of time to perform a discrete task Performance varies from one person to another, and varies due to the difficulty of the task, the amount of repetitions of the task, the motor skills of the individual and so forth. These complex issues are addressed by reducing the human computer interactions into simplified actions and by using empirical models, and data from prototypes and experimental studies.

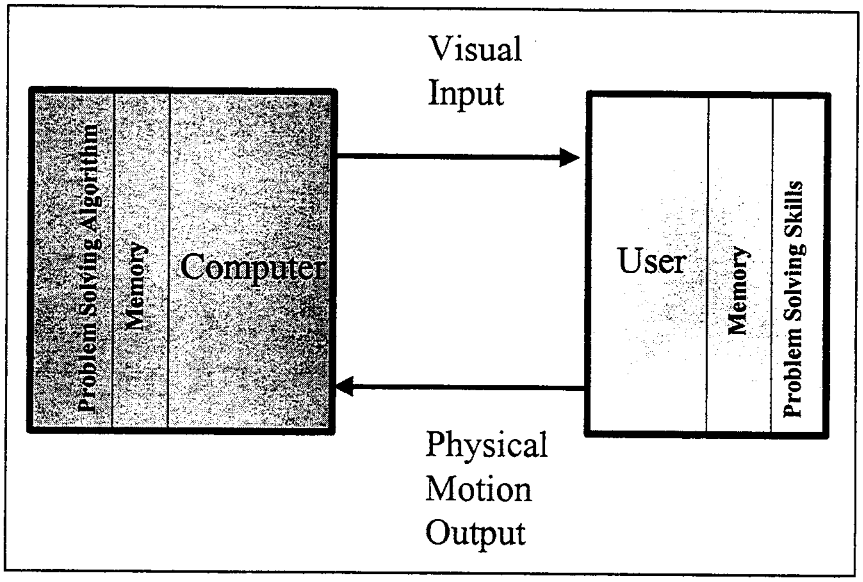


FIGURE 6.7: HUMAN COMPUTER INTERACTIONS ADAPTED FROM BLACKWELL [1999]

6.3.2 I/O: Visual Input and Motor Output

6.3.2.1 Visual Input

There has been much research with respect to the characteristics of human vision in the areas of physical reception, processing and interpretation. Understanding these various characteristics is important for computer graphic designs (e.g. sophisticated rendering algorithms in which 3-D models are converted into 2-D shaded representations) [Blackwell, 1999]. Areas of concern with respect to the physical reception of information and the information processing and interpretation are illustrated in Figure 6.8.

6.3.2.2 Motor Output

For human-computer interactions, the performance model for motor output focuses exclusively on limited hand/arm motions. The typical model is a representation of Fitts' Law [Blackwell, 1999;Green, 1997; Griffiths, 2002; Nunes, 2001], which is a simple, empirical model of the amount of time required to make *linear* hand and arm movements.

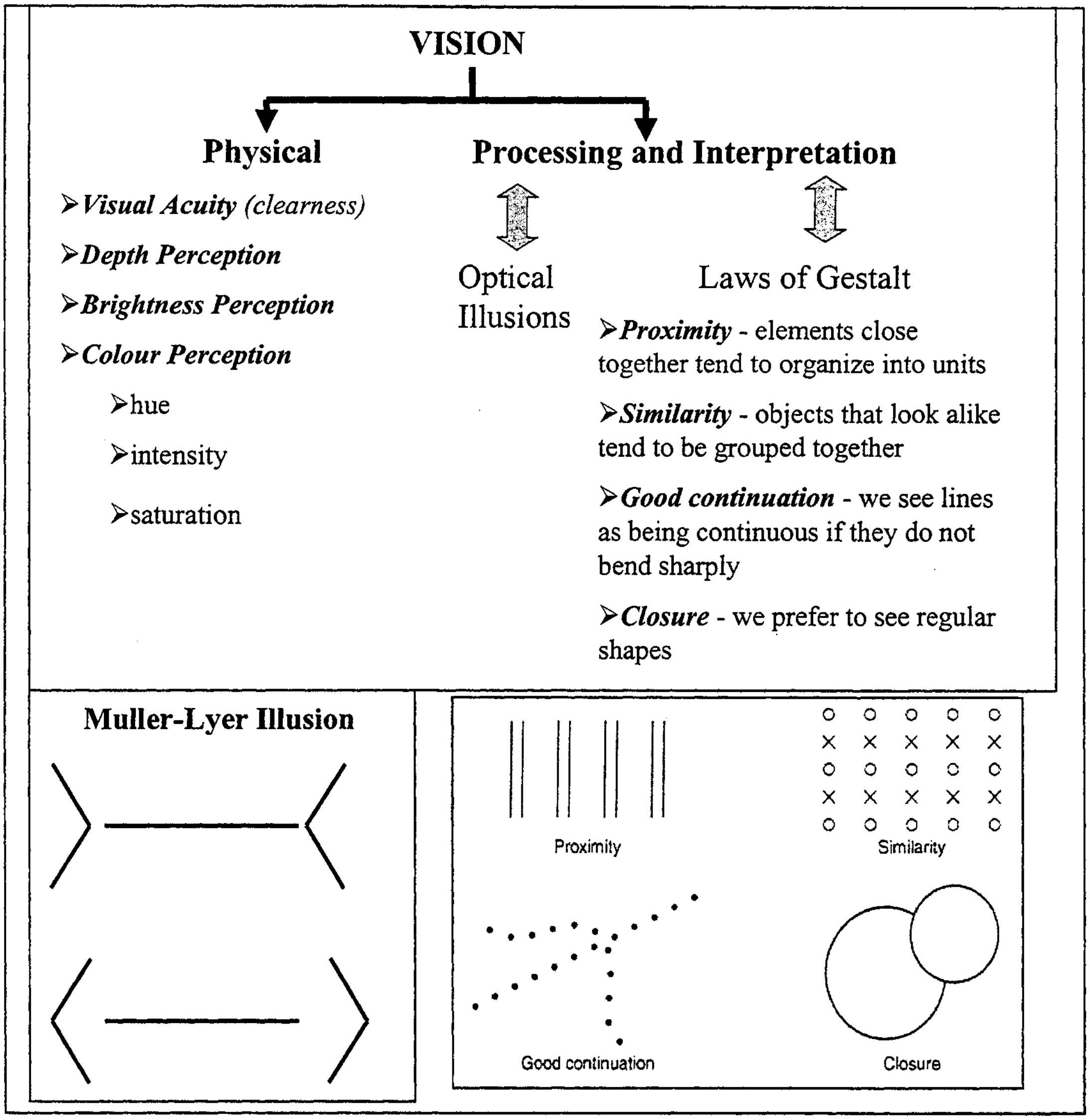


FIGURE 6.8: VISUAL INPUT FACTORS ADAPTED FROM BLACKWELL [1999] AND GRIFFITHS [2002].

The index of difficulty ID is related to the distance or amplitude A of the movement and the size or width W of the region where a valid "hit" occurs as shown in Figure 6.9. The unit "bits" appears to have no physical meaning.

$$ID = \log_2(2 \cdot A / W) \text{ bits [Fitts, 1950]} \quad (6.1)$$

The movement time MT is defined as:

$$MT = a + b \cdot ID \quad (6.2)$$

where a and b are determined experimentally.

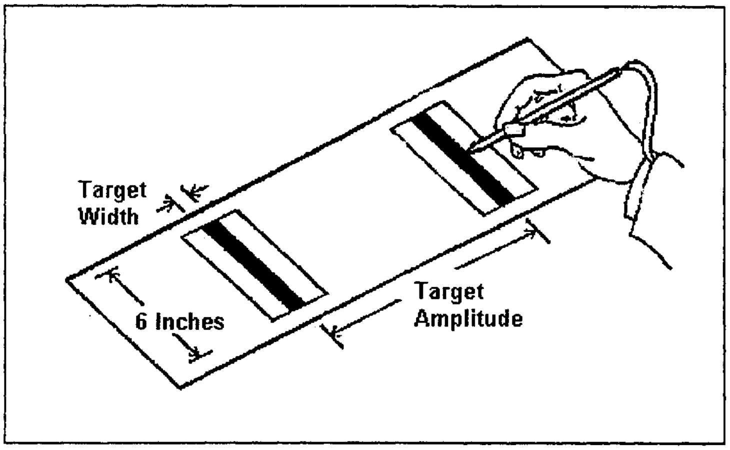


FIGURE 6.9: FITTS' EXPERIMENTAL TASK [MACKENZIE, 1995; FITTS, 1954]

For short motions or "easy " tasks (i.e. large target width) a negative index could result if A < W. In 1960, Welford refined the model by to the equation below [Felicano, 1995; MacKenzie, 1995]

$$ID = \log_2(A / W + 0.5) \tag{6.3}$$

Another modification presented in the literature is [Blackwell, 1999; MacKenzie, 1995]

$$ID = \log_2(A / W + 1) \tag{6.4}$$

This model always provides a positive result for the index of difficulty, and is the model used by several researchers [Blackwell, 1995; MacKenzie, 1995]. In must be noted that all versions of this model were developed for horizontal (non-angular) movements. For 2-D movements, the value of W is variable with respect to the approach angle as shown in Figure 6.10, and must be carefully considered. Fitts' law is a prediction model for rapid, aimed movement. It does not focus on accuracy, nor can it be used for other tasks such as using a joystick.

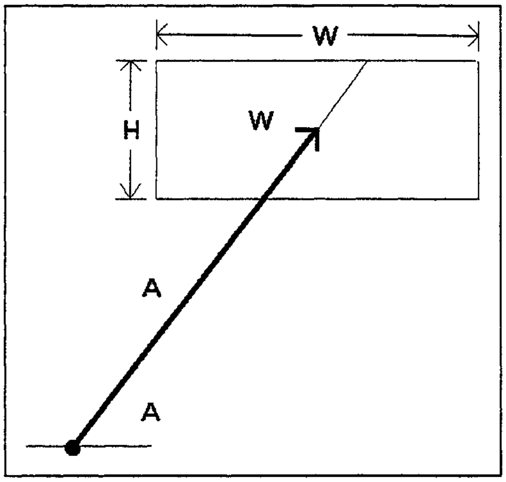


FIGURE 6.10: 2D CONSIDERATIONS FOR FITTS' LAW [MACKENZIE, 1995; FITTS, 1954]

6.3.3 Models of Memory

Recall from Chapter 5.5 that memory consists of three main subsystems: sensory memory, short-term or working memory and long-term memory. The two properties of concern are the memory size and the decay time – two variables very difficult to define and quantify, as there is no measurement for information content. Many experiments have concentrated on remembering letters. For this test, the results from Card et al for sensory memory decay time and size are shown in Table 6.1:

Sensory Memory	Decay Time	Size
Visual memory	200 [70 ~ 1000] msec	17 [7 ~ 17] letters
Auditory memory	1500 [900 ~ 3500] msec	5 [4.4 ~ 6.2] letters

TABLE 6.1: SENSORY MEMORY [GREEN, 1997; GRIFFITHS, 2002; NUNES, 2001]

Measuring the size of short term or working memory is difficult as it interacts with long-term memory. Short-term memory can be accessed rapidly but it decays rapidly. The capacity for working memory "chunks" (composite units of information) is limited (Miller's 7 ± 2). There is no capacity limit for long-term memory and it takes longer to access information from long-term memory. There are three main processes associated with the operation of long-term memory:

- Encoding and Storage (requires repeated exposure or rehearsal in working memory)
- Forgetting (due to decay or interference)
- Retrieval (recall or recognition)

6.3.4 Models of Problem Solving

There are many subtleties associated with problem solving: issues with how the problem is presented, an individual's biases or experiences or the period of time one has to ponder a problem all influence both the solution path and the final solution. This will not be discussed here. From artificial intelligence (AI) research, there are several problem-solving methods. Common methods are:

- Generate and test
- Means-Ends Analysis
- Problem Reduction

The "generate and test" problem solving method is a "trial and error" technique. The generator will produce all possible solutions, and the tester evaluates the potential solution and decides whether to accept or reject the solution. A good generator is complete, non-redundant and informed, generating solutions from known formula or heuristics.

The means-ends analysis model for problem solving is based on a generalized model of searching a state space. There is an initial state, a final state and several intermediate states between the initial and goal states. Problem solving consists of applying a sequence of operators or procedures that cause a transition from the initial state to reach the goal state, or at least to an intermediate state that reduces the difference from the current state to the goal state.

If there are no operations to achieve a goal directly using the "means-ends" analysis method, the goals are then decomposed into appropriate lower level sub-goals; hence the "problem reduction" formulation. This model of problem solving as a recursive hierarchy of sub-goals has been widely adopted as a basis for the analysis of human problem solving [Blackwell, 1999].

6.3.5 Uncertainty and Practice

6.3.5.1 Uncertainty

The time to make a decision is related to the degree of uncertainty of the decision. Hence to predict the amount of time to make a simple decision T_d is given by [Nunes, 2001; Green, 1997]:

$$T_d = I_c H \tag{6.5}$$

where I_c = 150 [0~157] msec/bit, and is an experimentally derived value, and

H = information-theoretic entropy (which was introduced by Claude Shannon in 1948 as a measure of information) [Shannon, 1948].

H can be used to determine of the degree of uncertainty or as a measure of the rate of information acquisition.

The time is takes to make a decision or choose between alternatives for n equally probable alternatives is given by Hick's Law [Nunes, 2001; Green, 1997]:

$$H = \log_2(n+1) \tag{6.6}$$

or

$$H = \sum_{i}^{n} p_i \log(1/p_i + 1) \tag{6.7}$$

where p_i = the probability of alternative i for n alternatives of unequal probability.

For a simple problem, humans do not linearly consider each alternative, but use a probability analysis to classify alternatives and to quickly pick the most viable solution, but as the amount of alternatives increase, so does the time to make a decision.

Blackwell [1999] uses Hick's Law as a measure of visual search for the time to find one item among a number of similar items (discounting pop-out effects such as a different colours or levels of brightness).

6.3.5.2 Power Law of Practice

Performance improves when repeating some physical or cognitive task over a period of time; consequently, the power law of practice, as given by equation (x), is another method for representing "reinforcement learning". If an operation requires T_1 seconds to perform the first time, then on the n^{th} cycle it will require T_n seconds. This improvement has been experimentally measured, and the empirical model for "practice" is [Nunes, 2001; Green, 2002]:

$$T_n = T_1 n^{-a} + b \qquad (6.8)$$

where a = .4 [0.2~0.6]

6.3.6 The Model Human Processor

The classical reference in the field of cognitive modelling in human-computer systems is "The Psychology of Human Computer Interaction" by Card et al (1983) [Grant, 1990; Green, 1997; Griffiths, 2002; Neerincx, 1995; Nunes, 2001; Wimmer, 2000] in which the "Model Human Processor" is introduced. The model human processor views the user as composed of three processors (perceptual processor, cognitive processor, and the motor processor) and four memories (visual memory, auditory memory, short term memory and long term memory) as illustrated in Figure 6.11. This model was used to predict the typical time (and the range) with which users could perform computer tasks.

The perceptual processor carries stimuli from the physical domain and buffers the information in the sensory memory while it is being encoded. The working memory receives the encoded information, and combines it with information retrieved from long-term memory, which has been previously encoded and stored.

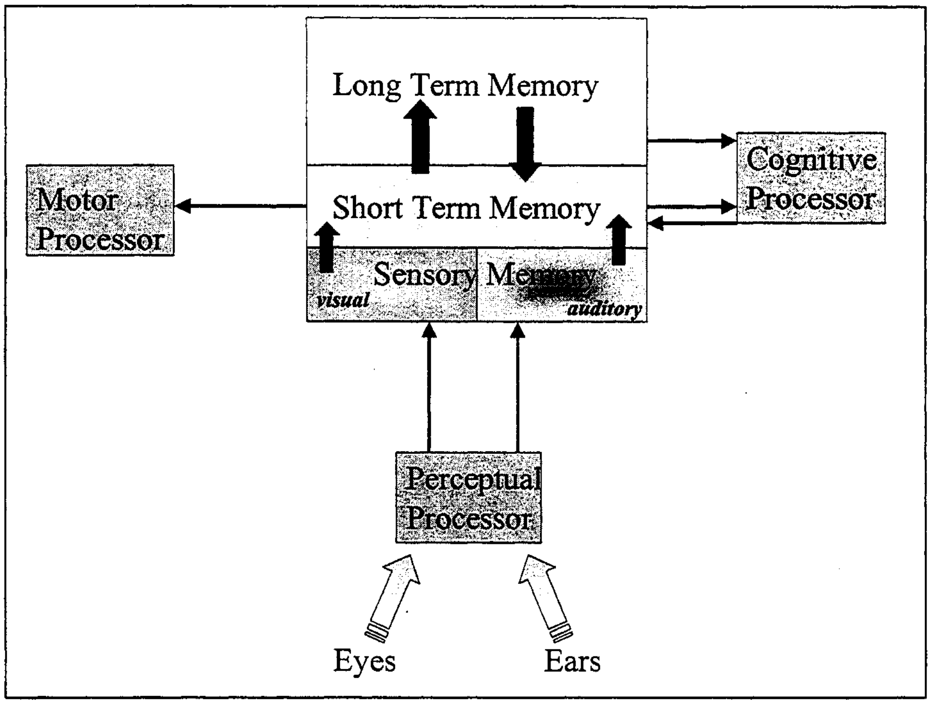


FIGURE 6.11: MODEL HUMAN PROCESSOR

The perceptual processor contains the two sensory memories, and the cognitive processor contains the working and long-term memories. Each processor can operate separately, and operate in parallel (driving, reading signs and listening to the radio) or sequentially. The total task time is estimated by adding the mean time for each processing event. From Card et al, the observed estimated mean times and ranges to make simple "instantaneous" decisions, perceiving a stimulus and making a simple tapping motion is shown in Table 6.2.

Cognitive Processor	70 [25 ~ 170] msec
Perceptual Processor	100 [50 ~ 200] msec
Motor Processor	70 [30 ~ 100] msec

TABLE 6.2: PROCESSOR CYCLE TIMES [BLACKWELL, 1999; GREEN, 2002; NUNES, 2001]

The total time required for human computer interaction is predicted by the simple equation:

$$T_{total} = n_c t_c + n_p t_p + n_m t_m \tag{6.9}$$

Card et al [Grant, 1990; Green, 1997; Griffiths, 2002; Neerincx, 1995; Nunes, 2001;] then refined their model to describe specific motor tasks (keystrokes T_k, pointing with a mouse T_p, homing T_h, and drawing T_d), the time for a user to make a decision T_m, and the system response time T_r. This model is called the Keystroke Level Model, and has been used to test text and graphics editors, and system utilities. The task time is now defined as:

$$T_{total} = T_k + T_p + T_h + T_d + T_m + T_r \qquad (6.10)$$

The keystroke model predicts basic actions. The mental operations are far more complex than one simple linear variable, and one user's methodology to obtain a goal will differ greatly from another user's.

6.3.7 Human Performance Models

6.3.7.1 Goals, Operators, Methods and Selection Model (GOMS)

Card et al [Blackwell, 1999; Grant, 1990; Green, 1997; Griffiths, 2002; Neerincx, 1995; Nunes, 2001] pioneered the GOMS model (Goals, Operators, Methods and Selection rules), which builds on the model human. The analysis of knowledge on how to perform the various tasks or the problem solving mechanisms is introduced with the GOMS model. GOMS provides a framework for modelling aspects of human cognition. Simply stated:

- Methods are used to achieve specific Goals.
- Methods are composed of Operators.
- Operators are specific tasks that are performed within a specific time period.
- More than one set of Methods can achieve the desired Goal; consequently, Selection rules are used to determine the appropriate Methods.

Once the task analysis is for a high level goal is completed, estimates of performance time are calculated based on the model human processor. This model of predicting human performance is based on a premise that human behaviour emulates a rational, information-processing system and that the cognitive activities are interpreted in terms of searching in a state space problem. In addition, the model can be used to predict the *effects* of errors on task performance as it can be assumed that recovering from an error involves similar GOMS components as the correct activities.

The GOMS framework has been extended into many other analysis techniques processor [Blackwell, 1999; Grant, 1990; Green, 1997; Griffiths, 2002; Neerincx, 1995; Nunes, 2001]. These techniques are used to provide insight into a system's usability by focusing on the task execution and learning times, functionality, operator sequences and error recovery. GOMS is a task analysis method that is effective for narrow, well-defined, routine cognitive tasks. It is time consuming to create a model for goals that contains a large set of tasks. GOMS is based on skill-rule behaviour, not knowledge behaviour. The model applies to skilled users, and does not address mental workload, fatigue, relearning, errors or system functionality. Interestingly, although Card et al introduced the model human processor and the GOMS framework, the two concepts do not seem to have many direct, correlating associations.

6.3.7.2 Skill, Rule and Knowledge Based Behaviour

Rasmussen developed another keystone framework for cognitive tasks analysis for computer based information and process controls within a complex industrial environment [Grant, 1990; Neerincx, 1995; Rasmussen, 1988, 1993]. This analysis is directed at optimizing human diagnosis and minimizing human errors by building systems that present relevant information in a clear, easily understandable format. The underlying principle of Rasmussen's model is that human behaviour is a goal-oriented activity, and the decision-making stages are not sequential, but occur as in a stepladder in which stages can be bypassed based on training and experience [Neerincx, 1995]. This model, as illustrated in Figure 6.12, complements the model human processor introduced by Card et al. The dashed arrows indicate where short cuts in the decision making process could occur based on the situation.

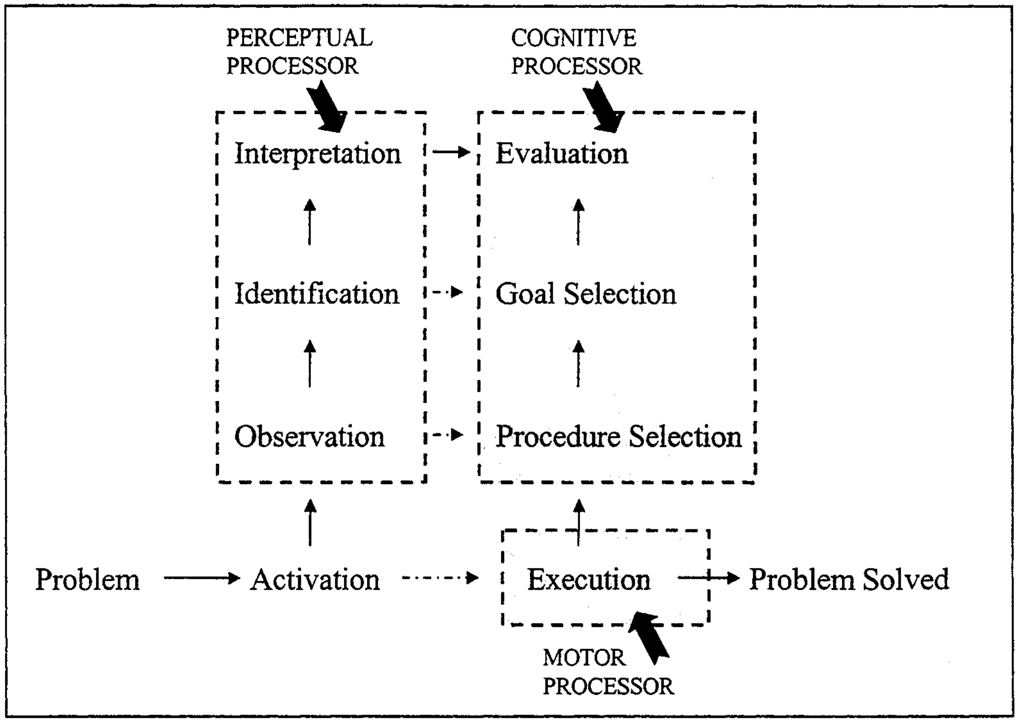


FIGURE 6.12: RASMUSSEN'S STEP LADDER MODEL OF DECISION MAKING ADAPTED FROM NEERINCX [1995]

Rasmussen presented a three-tier framework of cognitive processes that complements process control tasks which is summarized in Figure 6.13:

- low level rigid tasks → autonomous → fast response time→
    - automatic (or below the conscious awareness) ***skill*** based actions
- medium level tasks → associative → moderate response time →
    - solutions to a situation is governed by ***rules*** or heuristics (*if* state *x then* action *y*), which is learned through training or experience
- high level tasks → cognitive → slow response time →
    - novel situation with no pre-established rules or procedures required ***knowledge based reasoning*** which focuses on the state, the goals, and initiates actions to achieve the goals

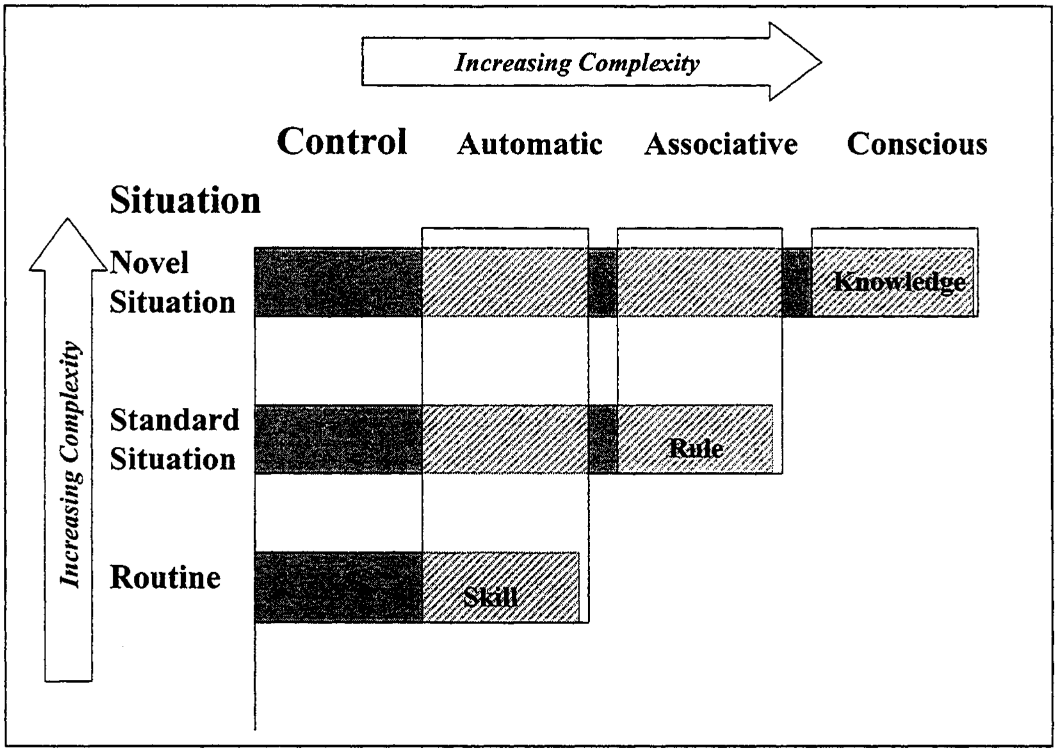


FIGURE 6.13: SKILLS, RULES AND KNOWLEDGE

Reason in 1990 [Busse and Johnson, 1889; Neerincx, 1995] used Rasmussen's skill-rule-knowledge classifications of human performance for a conceptual framework for error analysis: (1) slips and lapses and (2) mistakes. The Generic Error-Modelling System (GEMS) identifies three error types: skill based slips and lapses, rule-based mistakes and knowledge based mistakes, shown in Figure 6.14.

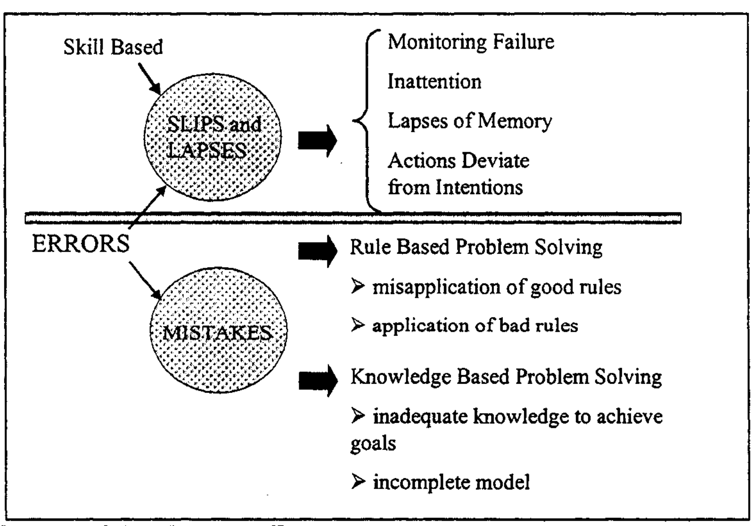


FIGURE 6.14: HUMAN ERRORS

Rasmussen and Reason focus on the cognitive mechanisms of task performance and the potential origin of errors, recognizing that within complex system errors (human-system mismatches) recurrently transpire. Human and equipment performance must be analysed as a system, not individually. The goal is the creation of error tolerant systems by providing features such as redundancy and robust error recovery mechanisms.

The distinction between the types of human error is critical, as different methodologies are required to manage each type of error. In aviation and process control, it has been realised that performance on the rule-based level is the least error-prone. Consequently, skill or knowledge based tasks should be appropriately supported. For example, knowledge based tasks should have the relevant information made available in a manner that is easily assimilated [Busse and Johnson, 1999].

6.3.8 Cognitive Architectures

6.3.8.1 Cognitive Complexity Theory

The Cognitive Complexity Theory (CCT), proposed by Kieras and Polson in 1985, is an extension of GOMS [Grant, 1990; Neerincx, 1995; Nunes, 2001]. The GOMS model focuses primarily on skills and simple procedures - there are no factors that quantify the amount of knowledge required to compare different tasks or to predict training times. According to the CCT model, when successfully solving a problem in a novel situation, new production rules are created linking the problem directly to a solution set. If the problem situation occurs again, the applicable production rules are applied (if *x* occurs then do *y*) as opposed to resorting to another problem solving scenario. The CCT model may be viewed as a computational model of rule based behaviour, which is the result of learning during problem solving [Neerincx, 1995]. This model assumes that these production rules are "cognitive units" and although different to learn, can be readily transferred to new tasks. Although the CCT model can be used to describe and possibly predict the learning time (usability) to use a software system, it does not provide direct performance predictions like the KLM model. As well, CCT does not model problem solving strategies or knowledge based behaviour.

6.3.8.2 State, Operator And Result (SOAR) Cognitive Architecture

SOAR is a general, cognitive architecture proposed by Newell and his colleagues. This architecture is able to work on open-ended problems and exploit problem-solving methods. The fundamental tenet is given by [Lehman et al, 2002]:

*BEHAVIOUR = ARCHITECTURE * CONTENT*

It is assumed that cognitive capabilities and behaviour are:

- goal oriented,
- require large body of knowledge,
- use symbols and abstractions,
- results are a function of the environment and knowledge base
- require learning from the environment and experiences.

SOAR is a unique production rule system – the principal mechanisms in SOAR process four elements: goals, "problem spaces", states and operators. A problem space is defined by a set of states (initial state, and one or more goal states) and operators, which are applied to a state (transforming states), relative to a specific goal. All cognitive acts are some form of search task; consequently in this architecture, all tasks are problems, which are solved by applying appropriate (rational) search operations within the problem space. All the systems knowledge is stated in the form of production rules [Grant, 1990; Neerincx, 1995; Nunes, 2001].

The "working memory" considers what problem space to use for the problem, what states within the state space might be under consideration, what selection of operators should be applied to the current state to attain desired states. In essence, SOAR utilizes recursive decision cycles within its architecture. To keep behaviour goal-directed, the succession of operators that are applied to the state and the resulting state transformations must be guided by the principle of rationality. [Lehman et al, 2002].

6.3.8.3 Adaptive Control of Thought (ACT) Cognitive Architecture

ACT is another general cognitive architecture developed by John Anderson and colleagues at Carnegie Mellon University [Grant, 1990; Neerincx, 1995; Nunes, 2001]. ACT distinguishes among three memory structures:

- declarative memory, which associates information and sequences;
- procedural memory, which is rule based; and
- working memory, which is the part of long term or procedural memory that is most actively used.

Unlike the SOAR architecture, in ACT all knowledge begins as declarative information, and procedural knowledge or inferences are "learned" through various mechanisms.

6.3.9 Cognitive Model Summary and Conclusions

There is no generic cognitive human performance model that has been developed to model human-computer interactions. The existing models aim at different goals. Because of these many perspectives, there are many techniques that have been developed which try to balance human-computer tasks to human abilities and knowledge. The models vary in complexity, and incorporate physical elements for "human I/O", and cognitive elements for information processing and problem solving.

GOMS [Blackwell, 1999; Grant, 1990; Green, 1997; Griffiths, 2002; Neerincx, 1995; Nunes, 2001] is a task analysis technique, which hierarchically decomposes goals into low level sub-goals, and would be cumbersome to describe anything other than routine, simple actions. GOMS models allow for qualitative and quantitative analysis of performance. This would help identifying design problems, although different levels of analysis would produce different results. A thorough GOMS analysis could predict the sequence of operations a user will perform a task (and consequently the performance time), predict learning time and evaluate the consistency of procedures (including error recovery) within the system designs. GOMS does not predict problem solving behaviour, individual differences or user preferences.

Rasmussen's [Grant, 1990; Neerincx, 1995; Rasmussen, 1988, 1993] skill-rule-knowledge models guidelines and a qualitative foundation for human task performance in man-machine systems. His focus is on the system design, information management and operational issues as opposed to direct human-computer interactions. Rasmussen is concerned with cognitive task loads and task complexity, where task complexity depends on size of problem space and the situational variability in problem solving [Neerincx, 1995]. Rasmussen and Reason focus on creating error tolerant systems within complex systems environment, such as providing redundancy and various error recovery strategies.

The Cognitive Complexity Theory, and the SOAR and ACT cognitive architectures were introduced more sophisticated analysis techniques to take into account a priori knowledge (CCT), learning and problem solving (SOAR and ACT). The cognitive architectures define how rules are interpreted, conditions for execution, and so forth; however, the cognitive architectures represent knowledge and information that is appropriate for problem solving tasks, but are not directly applicable for perceptual and motor tasks (human I/O).

Because of their initial assumptions, these models are limited in their range of applicability. As well, these models focus on individuals at a "micro level"; consequently, they are too limited in scope – the results of the models may not adequately reflect on the performance or functionality of the whole system. Other critical issues related to the effectiveness of these models are due to the capricious variations of human performance - users learn and forget, stress based on work load and time constraints influences behaviour, and typically there are conflicting goals.

Humans do not use hierarchical sub-routine logic and rules for making a decision → there several interrelating factors with human computational processes. This is demonstrated by the Stroop interference effect [Stroop, 1935].

Stroop

- performed research with word objects and the semantic content of the words
- created tasks involving colour naming and reading
- compared the time it took to read colour names printed in non-corresponding ink colours (the word red printed in blue ink, the word yellow printed in green ink and so forth) to a baseline reading of colour words in black ink.

→ **The task was more difficult (generated longer response times) when the word content conflicted or "interfered" with the colour recognition.**

FIGURE 6.15: STROOP EFFECT

Another approach to modelling human performance in a man-machine environment is to use systems design and analysis tools and techniques. The systems framework encompasses many elements and developmental phases within an organization, and looks at the "big picture". The building blocks for a systems design and analysis perspective include portions of the physical and cognitive human performance models, but the scope for the model and the results is much larger. Some models that utilize the systems approach and tools are presented in the next section.

6.4 Systems Analysis Methodology

6.4.1 Introduction

There are two broad but distinct environments that apply the systems approach: the military and business environments. The effectiveness of a mission or business depends on the successful exploitation of resources. Increasing demands must be satisfied using tools with increasing complexity and various levels of automation in a cost effective manner. An integrated system design which produces the best interactions must take several elements into account, including: anthropometrical and ergonomic data, physiological and psychological factors, and cognitive elements, which have been introduced in previous sections. All factors cannot be considered; however, initiating a systems development process for both the equipment and the human operators can augment the overall system performance.

The focus of the military systems is different from business production systems. Military objectives focus on unique missions with respect to attack, surveillance or defence systems. The level of intensity is heightened because of the potential life threatening situations. Business production systems are developed with the objective of maximizing financial gain: profits, cash flow, stock holder value, market share, and so forth. By nature, tasks are not as challenging in the business environment. However, both the military and business production systems must be stable, reliable, and perform on demand – and this includes the human element. How the systems engineering approach complements the human engineering aspects in both the military and business environments is shown in Figure 6.16.

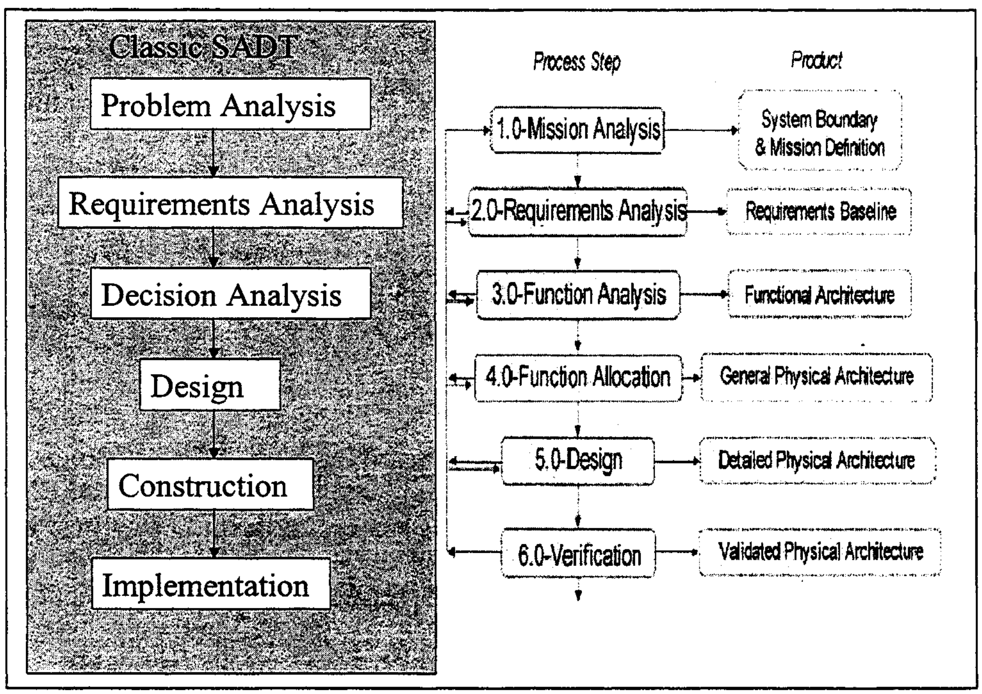


FIGURE 6.16: SYSTEMS ENGINEERING ADAPTED FROM U.S. DOD [1998]

6.4.2 Military Human Performance Systems

The U.S. Department of Defence has initiated and applied several human performance modelling programs, as illustrated in Figure 6.17. These programs target a specific system, and human cognition and performance are modelled through a variety of approaches and technologies. Some of these models focus on individual components of human performance at the detailed design level while others focus on the large-scale integration of components.

In general, these programs are concerned with the total system design: the whole system conceptualized as a single complex system, and the performance requirements of human operators are considered simultaneously with the design of the software and the hardware components.

For example, the MIDAS system has three sets of input models:

- a system model which focuses on the equipment (displays, controls, and equipment functionality;
- a mission model which includes the planned mission activities; and
- a human operator model, which includes physical, motor and cognitive characteristics.

There are three classes of outputs:

- ergonomic measures (reach, visibility, etc.)
- mission/operator performance measures (activity traces, task load timelines, resource conflicts, information flow - human to computer, human to human), and
- visualization of simulated missions (operator activities and the equipment states).

From the U.S. military viewpoint, success in future conflicts will be based on information superiority. This consists of superior knowledge, better decisions, and faster implementation to achieve strategic results. As operations are dispersed, personnel must be capable of rapid and independent movement within the cohesive whole. Ensuring future operational success will require an understanding of the nature of organizational collaboration and the demands on the "human in the loop" [Cannon-Bowers, 2000].

1970's **Navy**	***CAFES***
	*C*omputer *A*ided *F*unction *E*valuation *S*ystems
1980's **Air Force**	***CADET & CAT***
	*C*omputer *A*ided *D*esign and *E*valuation *T*ools
	*C*ockpit *A*utomation *T*echnology
1980's **Army**	**HARDMAN-III** tools
1980's **Navy**	***ATCS***
	*A*dvanced *T*echnology *C*rew *S*tation
Recent:	
	Air Force's *OASIS* program
	*O*perations *A*nalysis and *S*imulation *I*nterface *S*ystem
	NASA's *MIDAS* program.
	*M*an-*M*achine *I*ntegration *D*esign and *A*nalysis *S*ystems

FIGURE 6.17: U.S. MILITARY HUMAN PERFORMANCE SIMULATION PROGRAMS

Several human performance demands in the military environment are shown in Table 6.3. Future research goals include:

- the advanced capability to model individual and organisational knowledge management, and model teams,
- research into the training process to be able to predict realistic training needs, and
- the integration of the various human performance models to allow them to be reusable.

6.4.3 Business Human Performance Systems

There are several disjointed approaches to modelling human performance in the business environment. Each model or modelling technique is limited in scope and application. But conversely, more attention is being paid towards understanding the human performance characteristics beyond the ergonomic factors relevant to a particular situation.

1. More rapid decision making in a "knowledge-centric" and "reach-back" environment
2. More flexibility/adaptability-platform level
3. Increased ability to deal with ambiguity
4. Detailed understanding of crew member competencies
5. Rapid replacement of competencies due to rotation
6. More flexibility/adaptability-individual level
7. Better mechanisms for managing human resources (knowledge management)
8. Higher speed learning
9. Higher degrees of shared battle space (situational) awareness
10. Better distributed teamwork and coordination
11. Better distributed decision making
12. More knowledgeable war fighters

TABLE 6.3: REQUIREMENTS FOR HUMAN PERFORMANCE AND HUMAN SYSTEMS IN FUTURE STRATEGIC AND OPERATIONAL FRAMEWORKS [CANNON-BOWERS, 2000]

Underdown [1997] developed the Transform Enterprise Methodology (TEM) using a systems approach to transform small business enterprises from their current states to adapt to changing customer demands. There was a complex mixture of elements being analysed – above the process and technology components, the corporate cultural was also considered when creating a robust methodology. The enterprise engineering approach focuses on overall optimization and improvement of an enterprise. The TEM is a methodology to guide the process. The IDEF0 modelling technique was used to provide a rigorous, structured representation for the various activities of the TEM.

Kjellberg [1999] also focuses of the overall process efficiency, and narrows in on the fact that the real bottleneck in organizations is the lack of knowledge. Knowledge improvement strategies should be linked to manufacturing strategies to optimize manufacturing performance. Team learning and competence development is fundamental to this success. Knowing must be transformed into learning and further on to competence, and is illustrated in Figure 6.18.

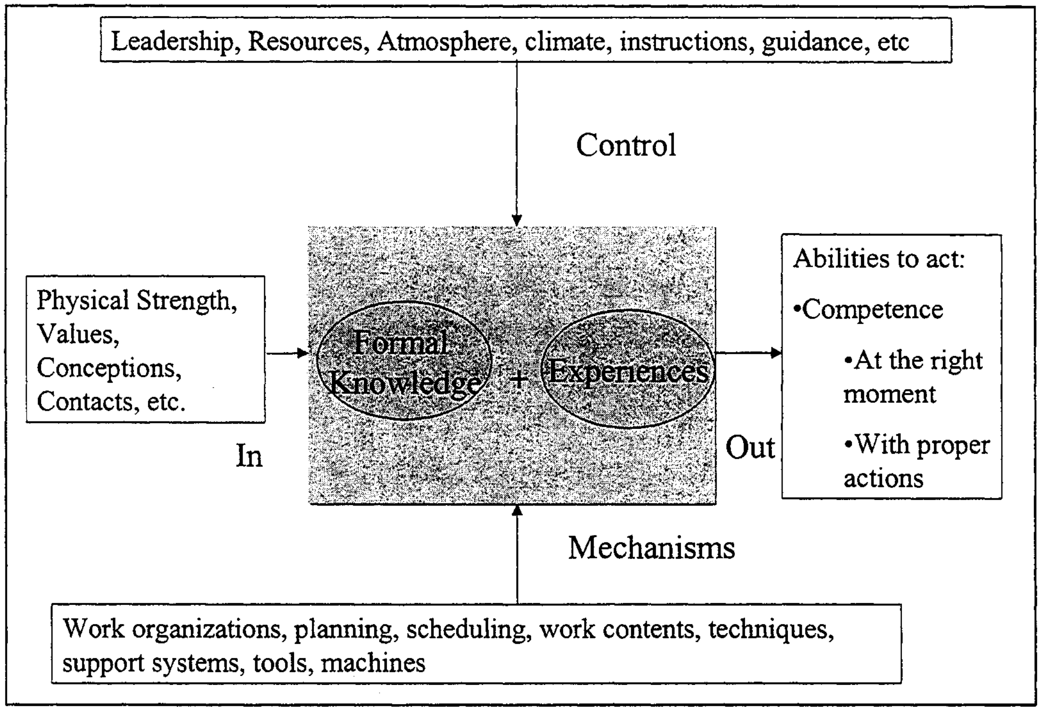


FIGURE 6.18: COMPETENCE, DEFINED BY SADT PRINCIPLES [KJELLBERG, 1999]

Competence management and teams of excellence are based on Modular Manufacturing Learning (MML). MML is the opposite of fragmented learning and work task division, which is typical work environment presented to unskilled workers. Every member within the environment is trained to be capable of performing multiple tasks. This "intellectual capital" must be developed through continuous learning, communication, management support and individual involvement and empowerment. The results should be innovative, responsive products and processes.

Kinnander et al [1998] modelled skill and competence development by applying learning curve theory to specific manufacturing simulations. Two different approaches were evaluated: (1) dedicated operators with limited skills and (2) broad operator competence. The results indicated that the learning phenomenon influences the results and that in an environment that undergoes constant reconfiguration, productivity and costs are directly influenced. The results of this simulation verify some of the concepts presented by Kjellberg and Abestam.

Niimi et al [1997] established that job flexibility did not correspond to job satisfaction and worker motivation in an automobile assembly plant. To address this issue, the nature of the vehicle assembly line layout, the process design and work tasks were re-evaluated by placing more consideration on the human factors. Work tasks were reorganized by: (1) creating independently operating work groups, and (2) generating on complete-process work assignments to be performed by these independent groups. Kjellberg and Abestam [1997] call these sub-assembly zones "free" workstations, as opposed to bounded workstations (Figure 6.19). The "free" work tasks utilize more of the worker's cognitive skills. This reduces apathy and stress for multiple reasons: there are several skills that must be learned and there is time for planning, problem solving and correction.

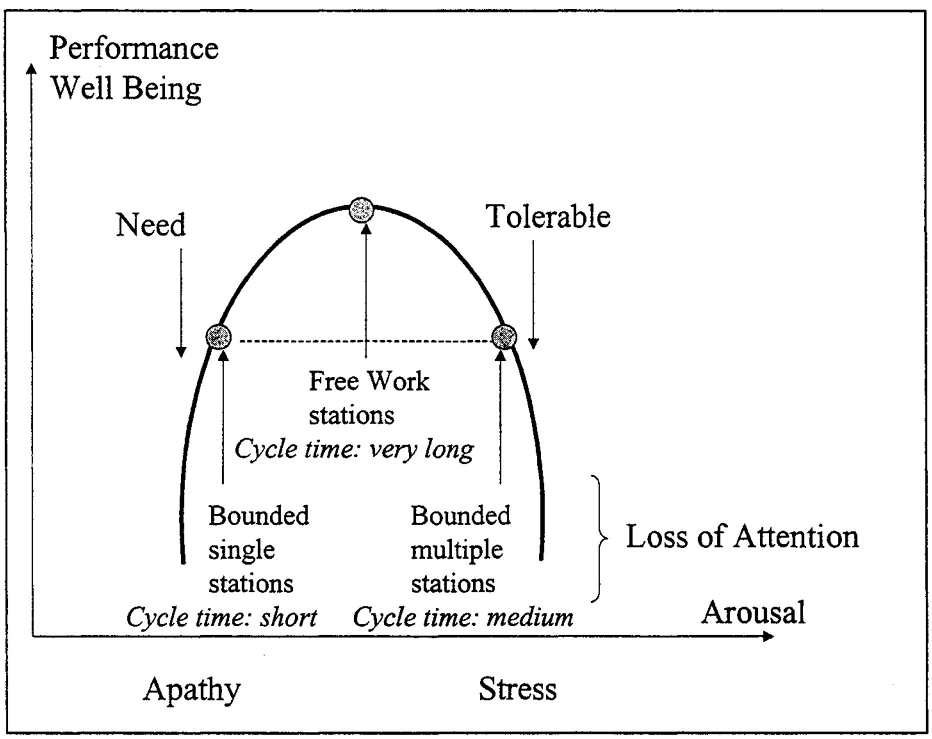


FIGURE 6.19: WORK TYPES AND PHYSIOLOGICAL ACTIVATION ADAPTED FROM KJELLBERG [1997]

In the physical domain, ergonomic studies were conducted to analyze workloads and the exertion duration time to quantify the strenuousness associated with loads and postures encountered with certain tasks [Niimi et al, 1997]. The goal was to reduce the workloads of all high-priority tasks in a systematic manner. To achieve this, simple in-line automation was introduced that augmented human performance. Data indicated that productivity and quality gains resulted was applying the concepts.

Okuda et al [1999] aim at being able to model human oriented production processes, and the benefits of cooperation between workers. Various line configurations were modelled to determine the influences of the line configuration with efficiency and interactions between workers. Their model was evaluated by studying the effects of cycle time fluctuations and multiple production manufacturing. The activities and the abilities of the workers had direct added value on the product. This production process had two distinct features: (1) there were several tasks performed by each operator and (2) there were long cycle times. These features allowed the operators to constantly assess and react to the immediate situation based on their judgment. It must be noted that for a single, static scenario, the line configuration had more productivity influence than the "cooperation" model. Many business and production related human performance models focus on the necessity of continuous learning and multiple skill sets. However, they do not provide a solid framework and a streamlined methodology to implement these aims.

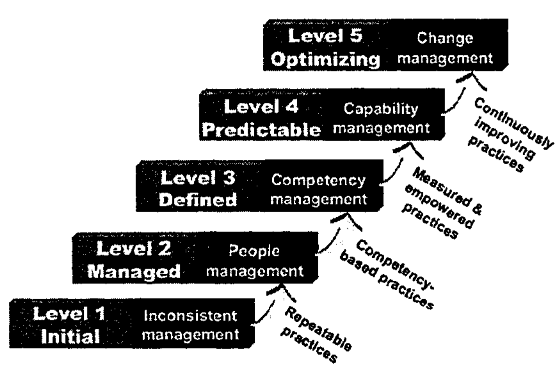


Figure 2.1 — The five maturity levels of the People CMM

FIGURE 6.20: P-CMM [CMU, 2002]

At Carnegie Mellon, researchers have addressed this by establishing the People Capability Maturity Model or P-CMM, which is a complementary framework to the Capability Maturity Model (CMM) (Figure 6.20). The CMM was introduced as a tool to assist in assessing the maturity level of an organization's information systems development. As the information systems within an organization matures, costs decrease and productivity increases. The CMM is a practical reflection of the organizational learning phenomenon. P-CMM has been developed to provide a multistage road map addressing people issues.

The P-CMM consists of an infrastructure of workforce processes and practices that aim at employee (and therefore business) growth. The foundation must be laid at one level before proceeding to the next level in order to achieve effective results.

6.4.4 Systems Models Summary and Conclusions

The effectiveness of an enterprise, be it in the military or production environments, depends on the successful exploitation of resources. The "intellectual capital" is as much of a resource as money, materials, software and hardware. The capability of each element in man-machine systems must be considered in conjunction with the interactions between the elements. Hence the military programs that focus on the interdependent physical and mental variables for a particular mission, and the similar production related projects [Niimi et al, 1997]. The military models concentrate on specific details at the micro level, whereas the production related models are more sweeping and generic in scope i.e. the models focus on general perceptions. Cognitive skill analysis, knowledge management, continuous learning and other human factors are not consistently modelled, nor are there compatibility between the various techniques. Each model is limited in scope due to the complex nature of the individual and the organization's environment.

Interestingly in the business models, there is shift from mass production techniques to "craft production" techniques. Although most models are application specific, two frameworks have been initiated: the Transform Enterprise Methods (TEM), and the People Capability Maturity Model (P-CMM).

The TEM is a formal model that explicitly defined a roadmap for understanding and growing small business enterprises to adapt to today's volatile market demands. IDEF0 modelling techniques were applied to rigorously illustrate the activities, their inputs and outputs, control factors and mechanisms. Using concepts introduced by the TEM and the IDEF0 modelling techniques, a model of an agile enterprise using reconfigurable manufacturing processes was developed, and is represented in Appendix B.

The P-CMM focuses on development and growth of people skills, but does not address man-machine integration issues. The production models initiated by Okuda, Kjellberg, Kinnander et al and Niimi et al touch on the necessity to understand the effects of physical and cognitive skills, learning and cooperation, realizing the immense potential for enterprise growth could result if the human resources were effectively exploited.

7.0 RESEARCH METHODOLOGY

7.1 Introduction

Many manufacturing models treat the human elements as though they were a machine resource. In reality, variable performance characteristics exist and are due to learning, fatigue, memory, the complexity of the task at hand, and skill set of the human elements. Cooperation and conflict are governed by individual personalities, the corporate culture and the work environment.

In the traditional manufacturing environment (using dedicated or adjustable manufacturing systems), periodic changes occur to both the product and the manufacturing processes, which lead to capital intensive investment, often in the realm of hundreds of millions of dollars. Typically, significant technology changes occur simultaneously – obsolescent equipment and processes are replaced with leading edge systems. Learning to manage the new system is a significant challenge. There are large learning curves for the individuals and the organization. Knowledge acquisition and transfer with respect to the new products and processes is slow. There is much information to be obtained and new skills to be learned by many different disciplines simultaneously. Between major retooling projects, changes are small scale and very localized.

At the other end of the spectrum with reconfigurable manufacturing systems, there is a dynamic utilization of resources that is constantly being reconfigured, whether at the micro level or at the macro level. A critical feature with this type of system is that the base modules are standardized and stable: learning is reduced and focuses only on the process or product modifications or innovations at the moment. Due to short product lifecycles "relearning" is constant with respect to product variations, but the skill set has been established for the basic modules within the organization; consequently, the rate of learning is much quicker. This has a direct relationship to success in the market place – the firm with a successful reconfigurable system will have both an advantage with lower initial costs, acceptance of change and sound quality (with respect to the manufacturing process) which leads to higher market shares. The relationship between skills and the time duration of the product run and the manufacturing environments is illustrated in Figure 7.1.

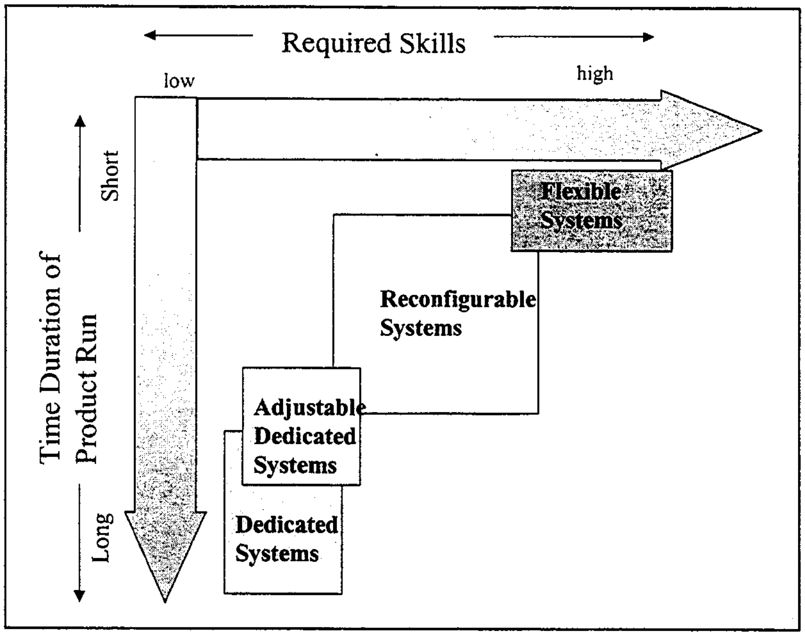


FIGURE 7.1: THE RELATIONSHIP BETWEEN SKILLS, TIME DURATION OF THE PRODUCTION RUN

7.1.1 Model for Participatory Manufacturing

A generic participatory system model for a manufacturing enterprise is illustrated in Figure 7.2. Existing models to do not include the worker performance and the variables which influence it as illustrated in Figure 5.9. Analogies of worker performance variations to manufacturing variations are:

- Normal human performance variation ↔ Normal machine variation
- Learning Curve ↔ Mean Time Between Failure, MTBF, and Mean Time to Repair, MTTR
- Affects of fatigue ↔ Unscheduled machine/tooling performance issues

What the definitions and mechanisms are for parameters like memory, learning or problem solving ability is not the essence of the problem for this project. The effects or *results* of these parameters need to be utilized for a participatory production model. The output variables for these intangible items must be functions with respect to time and costs. This in turn cascades into the standard production drivers (quality, uptime, machine utilization, etc.), which can be modelled by conventional techniques.

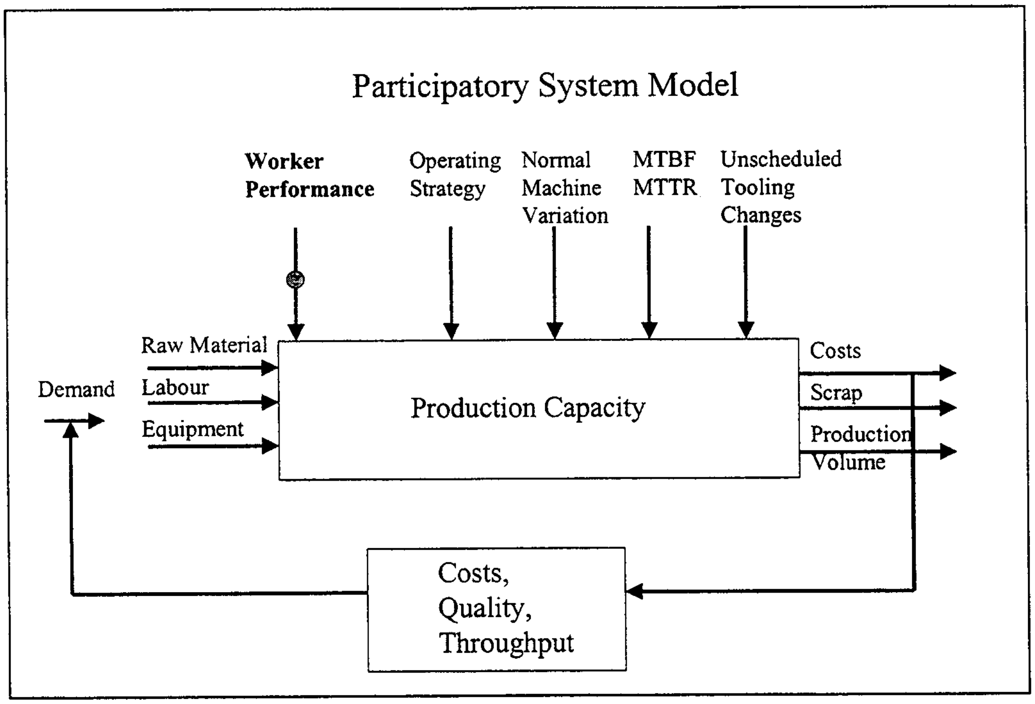


FIGURE 7.2: PARTICIPATORY SYSTEM MODEL

The learning curve phenomenon was used as the base model to explain human performance variation. The learning curve parameters are functions of various indices, which define product diversity, complexity, skills and experience, and so forth.

The standard learning curve represented in equation (5.1) will be used, but will be rewritten in a different format:

$$Y = KX^n \tag{5.1}$$

$$p_t(i) = p_t(1) \; * i^n \tag{7.1}$$

where $p_t(i) \rightarrow Y$, and is the time to produce the i^{th} unit or generate the i^{th} task.

$p_t(1) \rightarrow K$, and is the time to produce the first unit or generate the first task.

$i \rightarrow X$, and is the cumulative unit or task repetition number.

$n \rightarrow \dfrac{\log \Phi}{\log 2}$, and is the learning index.

$p_t(1)$ and n are both functions of work content or product diversity, complexity, effort, and human performance variables: skills, fatigue, and experience.

The fatigue curve from equation (5.2) will be modified to reflect that fatigue is a function of the learning rate, as shown below:

$$F(i) = \int f(i)di \tag{7.2}$$

For $i \geq$ critical value i_c, and $p_t\ (i) >$ critical value $p_t\ (i)_c$

This states that if the time to perform a task, $p_t\ (i)$ is greater than an acceptable limit, $p_t\ (i)_c$ (or conversely the performance output rate is less than or equal to a desired amount) at a critical cumulative value of i, (i_c) an increased workload is introduced to make up for the lost performance, which introduces a fatigue factor.

7.1.2 Learning Curve Parameter Estimation

The complexity of the model is quite evident based on the number and variability of influences that have been described above. Compounding the issue is that the effects of the various indices on the learning rate vary from individual to individual and situation-to-situation at the micro level, and similarly organization-to-organization at the macro level. The variables are interdependent, non-linear and dynamic. The general effects of the variables with respect to the learning rate and progress ratio are described below in Table 7.1.

Having a large progress ratio, or small learning rate factor is the ideal situation to improve performance and reduce costs. Yelle [1979] relates learning curves to direct labour hours only, but the learning curve also has a direct effect on quality and the system reliability. Figure 7.3 illustrates the learning rate and progress ratio.

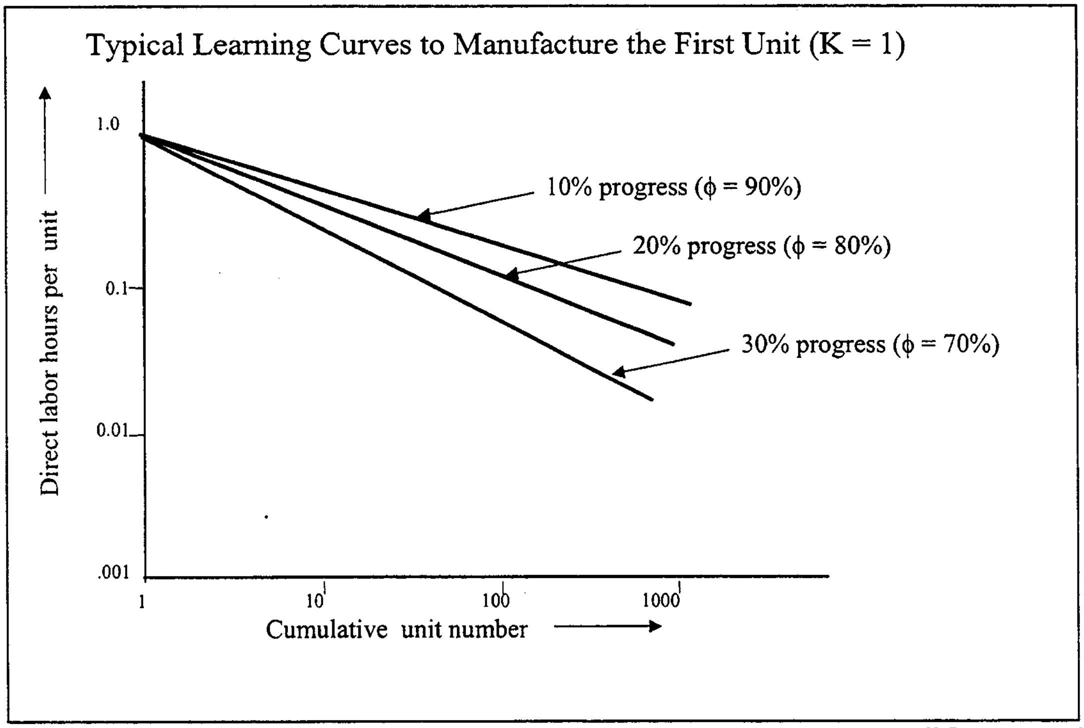


FIGURE 7.3: LEARNING CURVES ILLUSTRATING THE EFFECT OF "PROGRESS" [YELLE, 1979]

↑Complexity	↑ϕ - Learning rate ↓ Progress Ratio	More complex a product or process, the longer to learn the required knowledge to perform tasks and good decision making
↑Diversity	↑ϕ - Learning rate ↓ Progress Ratio	More diverse a product or process, the longer to learn the required knowledge to perform tasks and good decision making

TABLE 7.1: EFFECTS OF COMPLEXITY AND DIVERSITY ON THE LEARNING RATE AND PROGRESS RATIO

7.1.3 Research Methodology, Tools and Verification

These are the steps that were performed when executing this research:

1. Investigate the usability of the existing diversity and complexity indices for a human performance model, and refine as necessary.
2. Develop normalized "interaction charts" or utility charts that heuristically explain "cause and effect" phenomena for a complexity model.

3. Define indices that describe the employees' skill sets that convey more information than the standard statistical measures: "mean" and "standard deviation".

4. Develop task, attitude and corporate cultural measureables.

5. In tandem to items 3 and 4, develop normalized "interaction charts" or utility charts that heuristically explain "cause and effect" phenomena for human characteristics. These are presented in Appendix E.

6. Develop a model that relates learning curve parameters based on the complexity and skill indices.

7. Link the task, attitude and corporate cultural measureables into the learning curve model.

8. Test with production models at every step, analyse the results and generate conclusions.

9. Iterate as necessary to ensure a robust framework and methodology has been developed.

7.1.3.1 Tools and Verification

Basic spreadsheet, database and graphical analysis tools were used to aid in developing and refining the various indices and normalized "interaction charts" (such as EXCEL ®, ACCESS ® and MathLab).

Simple models based on the products illustrated in Figures 7.4 to 7.6 were used in order to be able to verify the "reasonableness" of the assumptions. As the model builds in complexity, more sophisticated tools and programming will become necessary.

7.1.3.2 Products

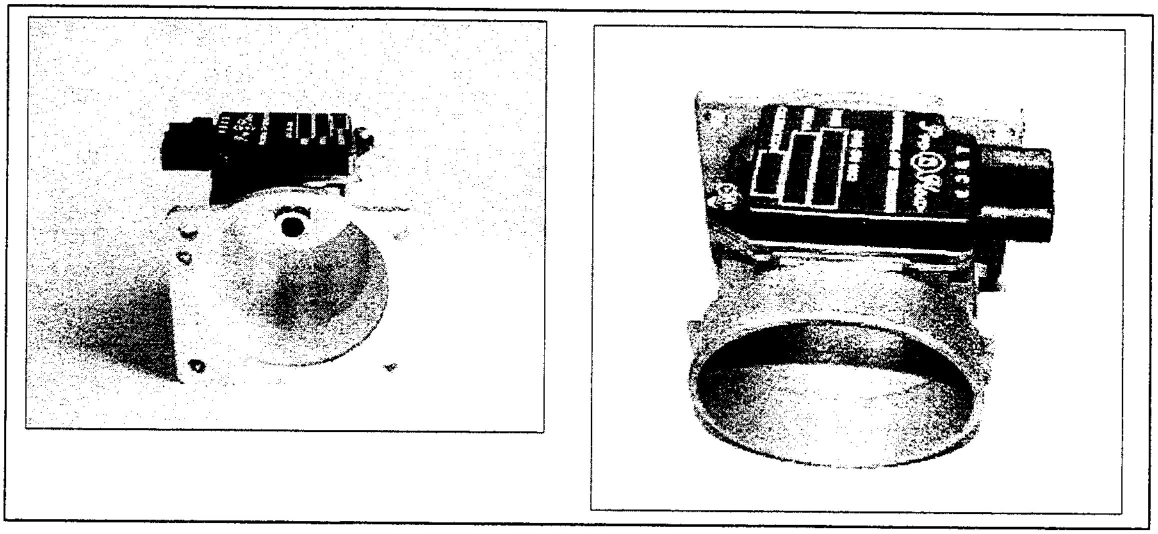


FIGURE 7.4A: MASS AIR FLOW BODY ASSEMBLY

MAF Body – Specifications

- ◈ Die Cast Aluminum
- ◈ 2 casting sizes → machining /assembly constant
- ◈ ~1,100,000 per year
- ◈ Prototypes and initial runs on CNC m/c's
- ◈ Full production - DMS pallet machine
- ◈ 4 parts per pallet
- ◈ Load – machine – wash – assemble - unload

FIGURE 7.4B: MASS AIR FLOW BODY PROCESS INFORMATION

V6 Push Rod Cylinder Block: Short Block

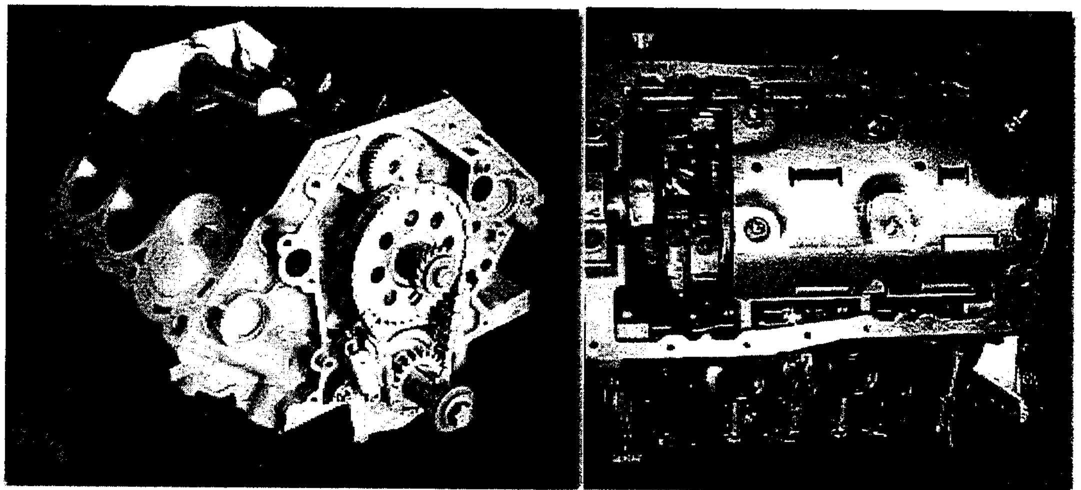


FIGURE 7.5A: V6 CAST IRON PUSH ROD CYLINDER BLOCK

V6 Cylinder Block – Specifications

- Cast Iron: 3 engine block options → 3.8L RWD, 3.8L FWD & 4.2L RWD
- ~150,000 per year
- Full production – AMS → 13 machines
- ~100 tapped holes
- Deep hole drilling → oil holes
- Projected tolerances → Head and MBC tapped holes
- Tight position, runout and diameter tolerances for the crank, cam and balance shaft bores, and dowel holes
- Tight Flatness spec. on the Bank faces, front face,& front thrust face
- Tight perpendicularity spec. for tappet bores to cam bore
- Cylinder bore specs → dia., cylindricity, etc.

FIGURE 7.5B: V6 CAST IRON PUSH ROD CYLINDER BLOCK PROCESS INFORMATION

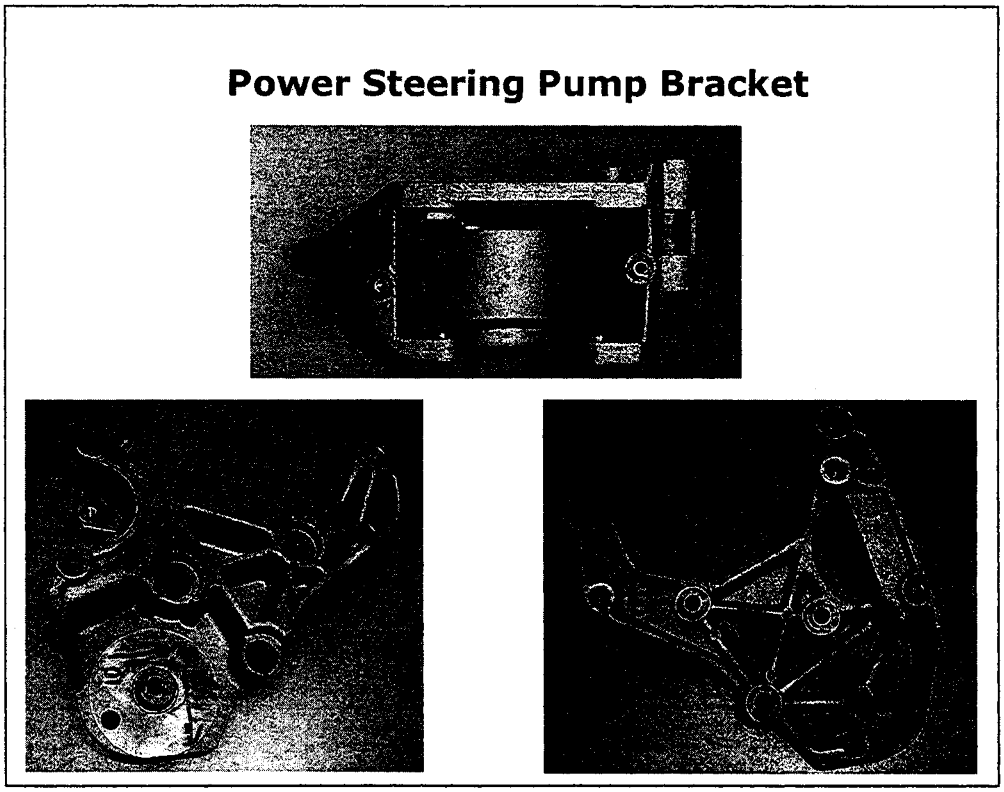


FIGURE 7.6A: CAST ALUMINUM POWER STEERING PUMP BRACKET

Power Steering Pump Bracket: Specifications

- Die Cast Aluminum
- 1 casting size
- ~60,000 per year
- Initial machining on CNC M/C's
- Increased volume production
  - 2 CNC M/C's → Bushing Assembly M/C **{24 hrs – 7 days}**
  - 1 CNC M/C → 1 Drilling M/C →1Drilling M/C →1 Tapping M/C→ Bushing Assembly M/C
- 4 parts per pallet for CNC M/C's

FIGURE 7.6B: POWER STEERING PUMP BRACKET PROCESS INFORMATION

7.2 Product Diversity Index

Recall from section 5.6 that the product diversity index (*PDI*) defined by Gollop and Monahan [1991] the j^{th} product is defined as:

$$PDI_j = 1 - \sum_{j=1}^{J} w_j^2 \qquad (5.3)$$

where w_j is the percentage of the j^{th} dissimilar product (option) in total production

The product diversity index has an upper and a lower bound. The upper bound occurs when the percentage of all dissimilar products is equal. The lower bound occurs when the percentage of one product is significantly greater than all others combined. The lower bound approaches zero. The upper bound PDI_U, shown in Figure 7.8, is represented by:

$$PDI_U = 1 - \frac{1}{J} \qquad (7.3)$$

where J is the number of dissimilar products (options) in total production. For example, for 5 dissimilar products, $0 < PDI \leq 0.8$.

An environment with a large product mix (area highlighted by a quadrilateral shape in Figure 7.7) would undergo constant set-ups and changeovers. Employees must have a good foundation of skill sets and good, systematic changeover procedures or the processes developed so that product differences are transparent (ideally) between one product and the next. Machine utilization and throughput would tend to be more critical than efficiency; this is a dynamic, constant learning environment.

In a zone dominated by one product (highlighted triangular area), the focus would be improving on the process efficiency to reduce waste and costs, as the environment is more stable. With the low percentage volume products, the efficiencies would tend not to be as high, as "relearning" would occur when those products are introduced into the system. These boundaries would fluctuate based on the manufacturing environment. The influence of the *PDI* on the initial production or task rates is illustrated in a utility chart in Appendix E.

↑Diversity (PDI → 1)	↑ϕ - Learning rate ↓ Progress Ratio	More diverse a product or process, the longer to learn the required knowledge to perform tasks and good decision making
↓Diversity (PDI → 0)	↓ϕ - Learning rate ↑ Progress Ratio	Large percentage of one product, learning rate is reduced, but "relearning" will occur on the low volume products

TABLE 7.2: PRODUCT DIVERSITY

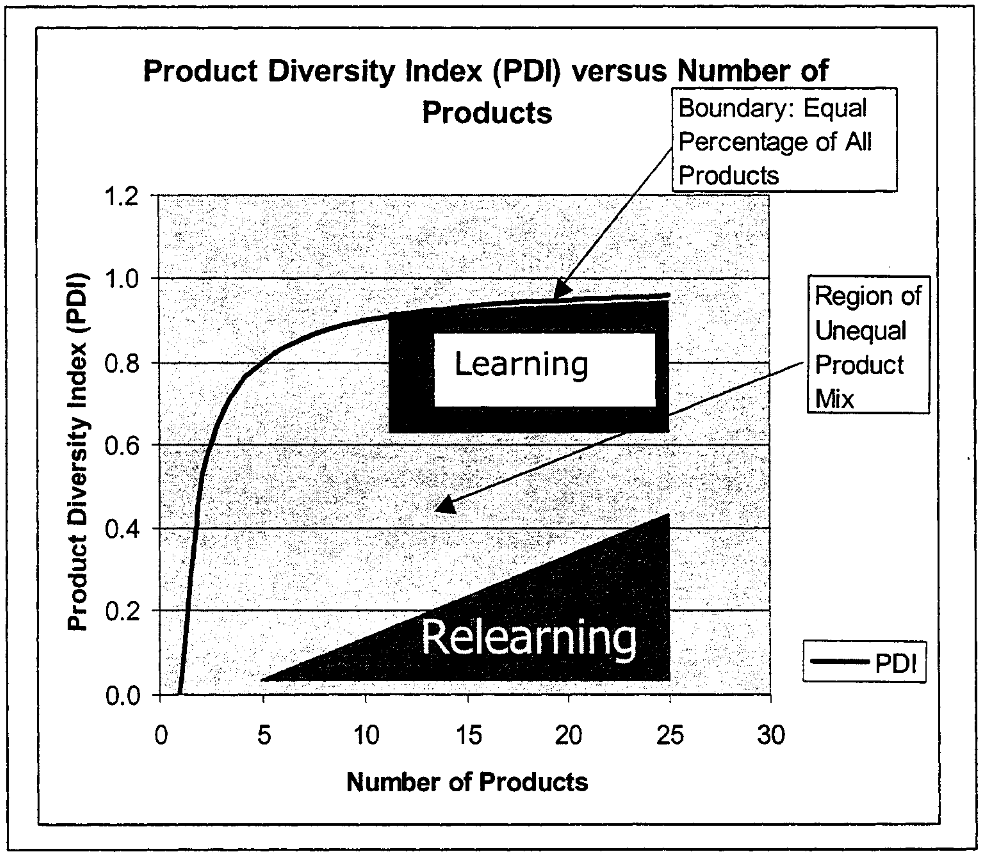


FIGURE 7.7: PRODUCT DIVERSITY INDEX VERSUS NUMBER OF PRODUCTS

The next item to consider is complexity. Complexity increases with the number and diversity of features to be manufactured, assembled and tested, the number, type and effort of the tasks, and so forth. Cooper et al [1992] measured the product complexity as the volume weighted average:

$$CI_j = c_j * x_j \Big/ \sum x_j \tag{5.4}$$

where c_j is the complexity value for product j, and x_j is the volume of product j.

But when using this relationship many issues exist. First, complexity is coupled with the percentage volume. This is misleading: product complexity tends to be higher with low volume products. In specialty job shops the part volumes are typically low, but the geometry of the product may be intricate with very tight tolerances (as with aerospace parts). Secondly, there is no distinction between different elements of product, process or task complexity. And finally, there is no systematic approach for determining the complexity coefficient c_j. The definition of the complexity index must be refined, and a systematic method determining a complexity measure is required: the method must be usable and consistent for different environments.

7.3 Complexity Index Method I

To start, it was assumed that complexity could be divided into two main categories: features (sub-components) and tasks. The features represent the final product; the diversity of the features would be due to the materials, geometry, special test requirements (for example appearance, no burrs, cleanliness, hardness, and torque levels) to achieve the final product (options), and so forth. The tasks represent the necessary work to produce the final product for any given process (including in-process steps). The complexity breakdown is illustrated in Figure 7.8.

To begin, the product complexity coefficient c_j is redefined as:

$$c_j = \frac{\sum_{f=1}^{F} c_{f,feature}}{F} \tag{7.4}$$

where c_f is the relative complexity coefficient of the feature, sub-component, process, etc.

F is the quantity of individual feature complexity coefficients

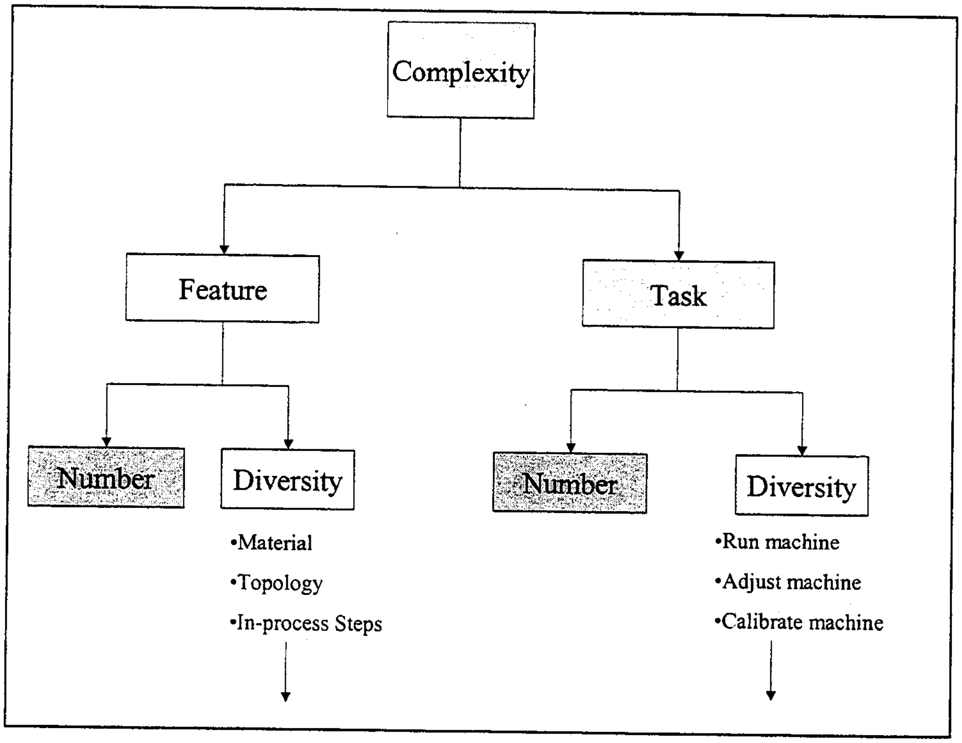


FIGURE 7.8: COMPLEXITY HIERARCHY

The relative complexity coefficient c_f is defined as:

$$c_f = \frac{F_N * F_D + T_N * T_D}{F_N + T_N} \tag{7.5}$$

where F_N is the quantity of features

F_D is the feature difficulty factor

T_N is the quantity of tasks

T_D is the task difficulty factor

$$F_D = \frac{\sum_{j=1}^{J} factor\_level_j}{J} \tag{7.6}$$

where F_D is the feature difficulty factor

J is the number of evaluation factors

$factor\_level_j$ is the factor for the j^{th} evaluation factor

$$T_D = \frac{\sum_{k=1}^{K} factor\_level_k}{K} \tag{7.7}$$

where T_D is the task difficulty factor

K is the number of task evaluation factors

$factor\_level_k$ is the factor for the k^{th} task evaluation factor

The factor level represents the "effort" to produce the feature or perform the task. The higher the effort (i.e. the more required stages or tools), the more complex the feature or task is. Each environment has a different perception of complexity, but is typically consistent within itself. Therefore it was decided to use a multi tier ranking system where low, medium, and high effort levels correspond to factor levels 0, 0.5 and 1 respectively. Alternatively, a 1-10 scale could be used, with the final "difficulty factor" value normalized by the maximum value of the scale. Selection of the ranking system is the first step in the methodology developed below, and illustrated in Figure 7.9:

1) Define the multi-tier ranking system to be used for the analysis.
2) Define the number *(F)* and type of individual features, components, sub-components, etc.
3) Determine the specific quantity of each feature defined in step 2.
4) Define the number and type of diverse "aspects" for evaluating the features *(J)* and the tasks *(K)* associated with manufacturing the product.
5) Generate the *FxJ* feature matrix and the *FxK* task matrix and assign the appropriate complexity levels into each cell, as shown in Figure 7.9.
6) Calculate the feature complexity coefficient c_f and the product complexity coefficient c_j, as defined by equations (7.4) to (7.7).

Using the Mass Air Flow Body (MAFB) as an example (Figures 7.4a, 7.4b, and 7.9), the product complexity coefficient c_j=0.31. When performing the analysis on the V6 Cylinder Block (Figures 7.5a, 7.5b, and 7.10), the product complexity coefficient c_j=0.41.

60 mm Aluminum Mass Air Flow Body					
Low Volume DMS line - 4 parts per pallet					
	Number	Mill	Drill	Tap	Bore
Front Face - Mill	1	4			
Sensor Face - Mill	1	4			
Sensor Mount Holes - drill, tap	2		8	8	
Plate Mount Holes - drill, tap	2		8	8	
Profile holes - drill, bore	2		8		16
Assemble Plate	1				
Amount per Pallet	4				
SUM		8	24	16	16

Description	**Features J = 5**							
	Number	**Diversity**						
		Material	Topology	Geometry	In-process steps	Tolerances	**SUM**	**D/J**
Tapped holes	16	0	0	0	0	0	0	0.00
Drilled holes	0	0	0	0	0	0	0	0.00
Bored holes	8	0.5	0	1	0	0.5	2	0.40
Milled surfaces	8	0	0	0.5	0	0	0.5	0.10
Assembly	4	1	1	0	0	0	2	0.40

	Tasks K = 5							
	Number	**Diversity**						
		Change Tools	Gage Features	Run Stations	Adjust Machines		**SUM**	**D/J**
					Mech.	Controls		
Tapped holes	16	0	0.5	0.5	0	0	1	0.20
Drilled holes	24	0.5	0	0.5	0	0	1	0.20
Bored holes	8	1	0.5	0.5	0.5	0.5	3	0.60
Milled surfaces	8	0	0.5	0.5	0	0	1	0.20
Assembly	4	1	0	1	1	1	4	0.80

	Feature Complexity
Tapped holes	0.10
Drilled holes	0.20
Bored holes	0.50
Milled surfaces	0.15
Assembly	0.60
Product Complexity	**0.31**

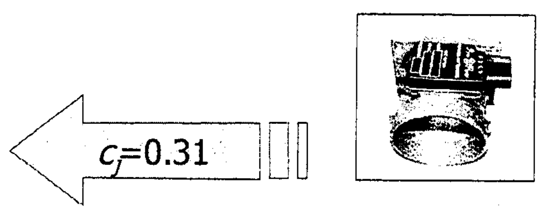


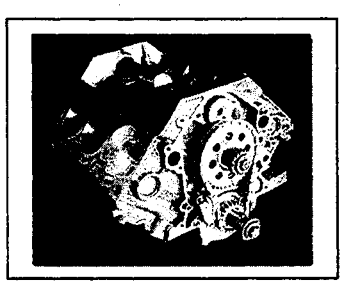
FIGURE 7.9: COMPLEXITY MATRIX EXAMPLE

The cylinder block is significantly more complex than the MAFB. To compare two or more products directly, the ranking method, factor level values and the skeleton of the matrix must be consistent between products. In Figures 7.10, 7.11 and 7.12 there is a comparison between the two products. Even if the technology or the process plan to produce the products are significantly different, proper selection of rows and complexity levels in the tasks matrix can reflect a relative complexity measure.

V6 Push Rod Cylinder Block

Description	**Features J = 5**							
	Number	**Aspects**						
		Material	**Topology**	**Geometry**	**In-process steps**	**Tolerances**	**SUM**	**D/J**
Tapped holes	101	0	0	0	0.5	0	0.5	0.10
Deep Drilled Holes	15	0	0.5	1	0.5	0.5	2.5	0.50
Drilled holes	5	0	0.5	0	0	0.5	1	0.20
Reamed holes	28	0	0	0.5	0.5	0.5	1.5	0.30
Bored holes	7	0.5	0	0.5	1	1	3	0.60
Honed holes	6	0.5	1	1	1	1	4.5	0.90
Broached surfaces	19	0	0.5	1	0	0.5	2	0.40
Milled surfaces	5	0	0.5	0.5	0.5	0.5	2	0.40
Assembly	12	0	0	0	0	0	0	0.00
Test	4	0	0	0	0	0	0	0.00
	Tasks K = 5							
	Number	**Aspects**						
		Change Tools	**Gage Features**	**Run Machines**	**Adjust Machines**		**SUM**	**D/J**
					Mech.	**Controls**		
Tapped holes	101	0	1	0.5	0.5	0	2	0.40
Deep Drilled holes	15	0.5	0.5	0.5	0.5	0	2	0.40
Drilled holes	144	0.5	0.5	0.5	0.5	0	2	0.40
Reamed holes	28	1	0.5	0.5	0.5	0	2.5	0.50
Bored holes	46	1	1	1	1	0	4	0.80
Honed holes	6	1	1	1	1	1	5	1.00
Broached surfaces	19	0.5	0.5	0.5	0	0	1.5	0.30
Milled surfaces	10	0.5	0.5	0.5	0.5	0.5	2.5	0.50
Assembly	12	0	0.5	0	0	0	0.5	0.10
Test	4	0		0	0	0.5	0.5	0.10

	Feature Complexity
Tapped holes	0.25
Deep Drilled holes	0.45
Drilled holes	0.39
Reamed holes	0.40
Bored holes	0.77
Honed holes	0.95
Broached surfaces	0.35
Milled surfaces	0.47
Assembly	0.05
Test	0.05
Product Complexity	**0.41**



c_j=0.41

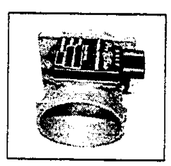
FIGURE 7.10: COMPLEXITY ANALYSIS – V6 CYLINDER BLOCK

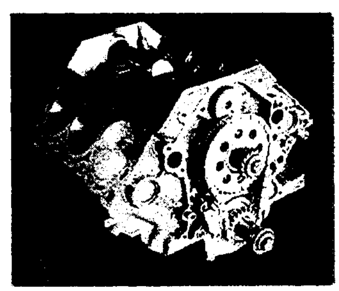
MAF analysis using V6 Cylinder Block Matrix

Description	Features J = 5							
	Number	Aspects						
		Material	Topology	Geometry	In-process steps	Tolerances	SUM	D/J
Tapped holes	16	0	0	0	0	0	0	0.00
Deep Drilled holes	0	0	0	0	0	0	0	0.00
Drilled holes	0	0	0	0	0	0	0	0.00
Reamed holes	0	0	0	0	0	0	0	0.00
Bored holes	8	0.5	0	1	0	0.5	2	0.40
Honed holes	0	0	0	0	0	0	0	0.00
Broached surfaces	0	0	0	0	0	0	0	0.00
Milled surfaces	4	0	0	0	0	0	0	0.00
Assembly	4	1	1	0	0	0	2	0.40
Test	0	0	0	0	0	0	0	0.00

	Tasks K = 5							
	Number	Aspects						
		Change Tools	Gage Features	Run Machines	Adjust Machines		SUM	D/J
					Mech.	Controls		
Tapped holes	16	0	0	0.5	0	0	0.5	0.10
Deep Drilled holes	0	0	0	0	0	0	0	0.00
Drilled holes	24	0.5	0	0.5	0	0	1	0.20
Reamed holes	0	0	0	0	0	0	0	0.00
Bored holes	8	1	0.5	0.5	0.5	0.5	3	0.60
Honed holes	0	0	0	0	0	0	0	0.00
Broached surfaces	0	0	0	0	0	0	0	0.00
Milled surfaces	4	0	0	0.5	0	0	0.5	0.10
Assembly	4	1	0	1	1	1	4	0.80
Test	0	0		0	0	0	0	0.00

	Feature Complexity
Tapped holes	0.05
Deep Drilled holes	0.00
Drilled holes	0.20
Reamed holes	0.00
Bored holes	0.50
Honed holes	0.00
Broached surfaces	0.00
Milled surfaces	0.05
Assembly	0.60
Test	0.00
Product Complexity	0.14





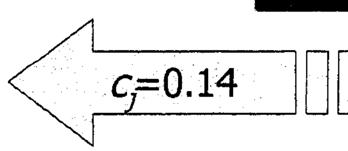


FIGURE 7.11: COMPLEXITY – MASS AIR FLOW BODY USING V6 CYLINDER BLOCK MATRIX

The analysis matrix identifies features and task elements that are common for the Mass Air Flow Body analysis and the Cylinder Block analysis. If a final feature for the product was not produced by a specific operation, (i.e. drilling) the value is set to zero, although it may be an in-process operation. Specific tasks are associated with all operations: in-process and final; consequently, values associated with the process tasks and the features will not necessarily match.

Using a comparative matrix format, the final MAFB analysis shows the product complexity coefficient c_f=0.14 (Figure 7.11), which is much more reasonable when compared to the cylinder block. When comparing the machining process only, the product complexity coefficients were 0.10 and 0.50 for the MAFB and cylinder block respectively (Figure 7.12).

Relative Complexity

Machining only:
MAF → c_f = 0.10
Block → c_f = 0.50

MAF Body

	Feature Complexity
Tapped holes	0.05
Deep Drilled holes	0.00
Drilled holes	0.20
Reamed holes	0.00
Bored holes	0.50
Honed holes	0.00
Broached surfaces	0.00
Milled surfaces	0.05
Assembly	0.60
Test	0.00
Product Complexity	0.14

Block

	Feature Complexity
Tapped holes	0.25
Deep Drilled holes	0.45
Drilled holes	0.39
Reamed holes	0.40
Bored holes	0.77
Honed holes	0.95
Broached surfaces	0.35
Milled surfaces	0.47
Assembly	0.05
Test	0.05
Product Complexity	0.41

FIGURE 7.12: COMPARISON OF COMPLEXITY

The relative complexity coefficient c_f can be extended into the general format, illustrated by Figure 7.13 and defined below:

$$c_f = \frac{X_{1,N} * X_{1,D} + X_{2,N} * X_{2,D} + X_{3,N} * X_{3,D} \ldots X_{M,N} * X_{M,D}}{X_{1,N} + X_{2,N} + \ldots X_{M,N}} \tag{7.8}$$

where $X_1 \ldots X_M$ are the complexity components to be analysed from *1* to *M*.

$X_{M,N}$ is the quantity of elements for the complexity for the complexity component X_M

$X_{M,D}$ is the diversity factor for the complexity for the complexity component X_M

Upon developing matrices to generate a product complexity coefficient using equation 7.8, some drawbacks immediately became evident:

1) Extensive detail is required when generating the matrix elements;
2) Several rows had a value of zero, which drove the complexity coefficient towards zero, essentially attenuating the values;
3) No weighting factor based on the percentage of the dissimilar features;
4) No factor exists that establishes how the amount and diversity of information affects the product complexity; and
5) Product, process and operational elements of complexity are interlinked.

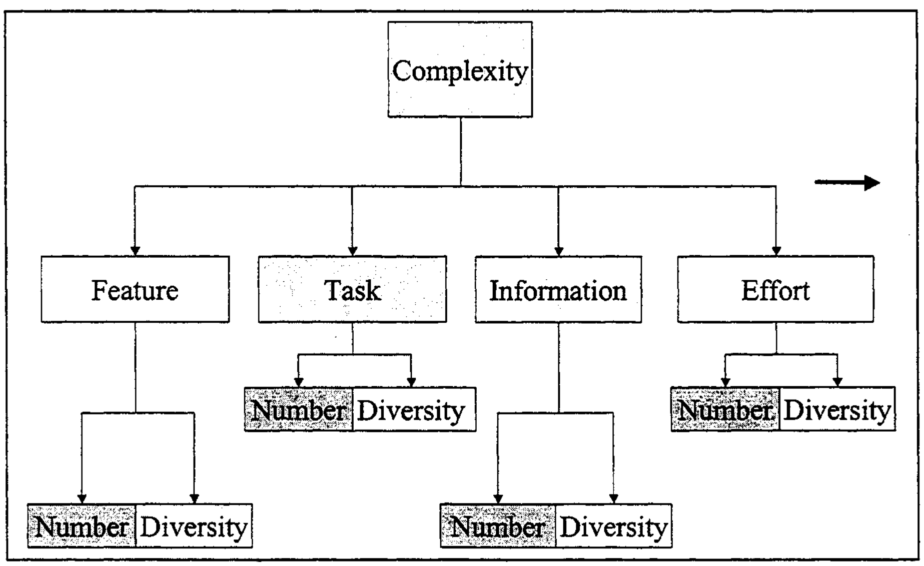


FIGURE 7.13: GENERIC COMPLEXITY HIERARCHY

Therefore, another framework needed to be developed that addresses these issues. This is presented in the next section.

7.4 Complexity Indices Method II

In the previous method too many facets of complexity were combined, resulting in the loss of meaning for the final result. Another perspective is needed. For example, manufacturing a standard tapped hole is not complex; however, a cylinder block can have approximately 100 tapped holes. Managing this quantity of information is complex. Conversely, a V6 cylinder block only has 6 cylinders; however, the final tolerances are extremely tight, and surface finish specifications are intricate. Much effort is needed to produce consistent final results. The concept of complexity needs to be extended to capture both these extreme cases. Based on this, it is assumed that complexity is a function of three main elements: the quantity of information, the diversity of the information, and the information content, as illustrated in Figure 7.14. The information content defined here should not be confused with the information content defined by Suh for the "Axiomatic Design Theory" [Suh, 2001]. Here information content is defined as a "relative" measure of effort to achieve the required result, not a measure of the probability of success.

There are three types of complexity to be considered in a manufacturing environment: product complexity, process complexity and operational complexity, and each one flows into the other. The cascading relationship is shown in Figure 7.15.

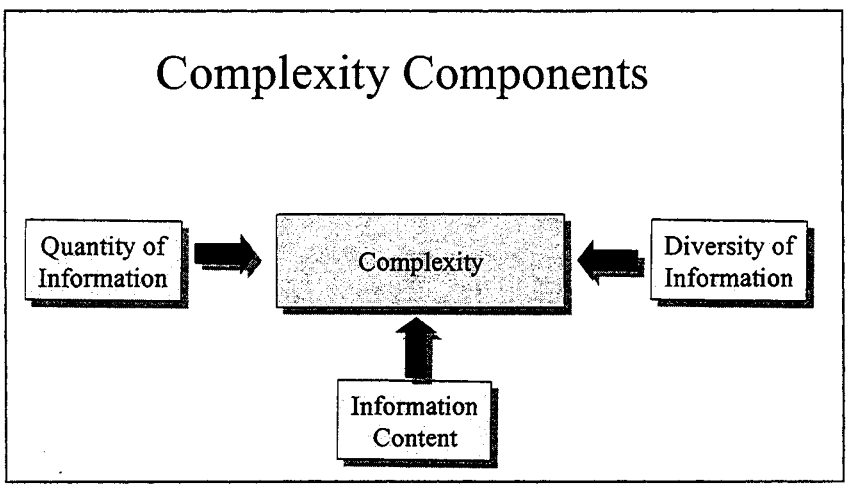


FIGURE 7.14: ELEMENTS OF COMPLEXITY

Product complexity is a function of the material, design and special specifications for each component within the product. Process complexity is a function of the product, the volume requirements, and the work environment. The work environment dictates the process decisions such as type of equipment, in-process steps, jigs, fixtures, tooling, gauges and so forth. Operational complexity is a function of the product, process and production logistics. The performance metrics, scheduling, equipment set-up, running, monitoring and maintenance tasks of the process are all components of operational complexity. **Complexity elements that deal with scheduling and production control decisions are beyond the context of this work.** A framework needs to be developed that generates an index (or indices) that addresses these facets of complexity, and it presented below.

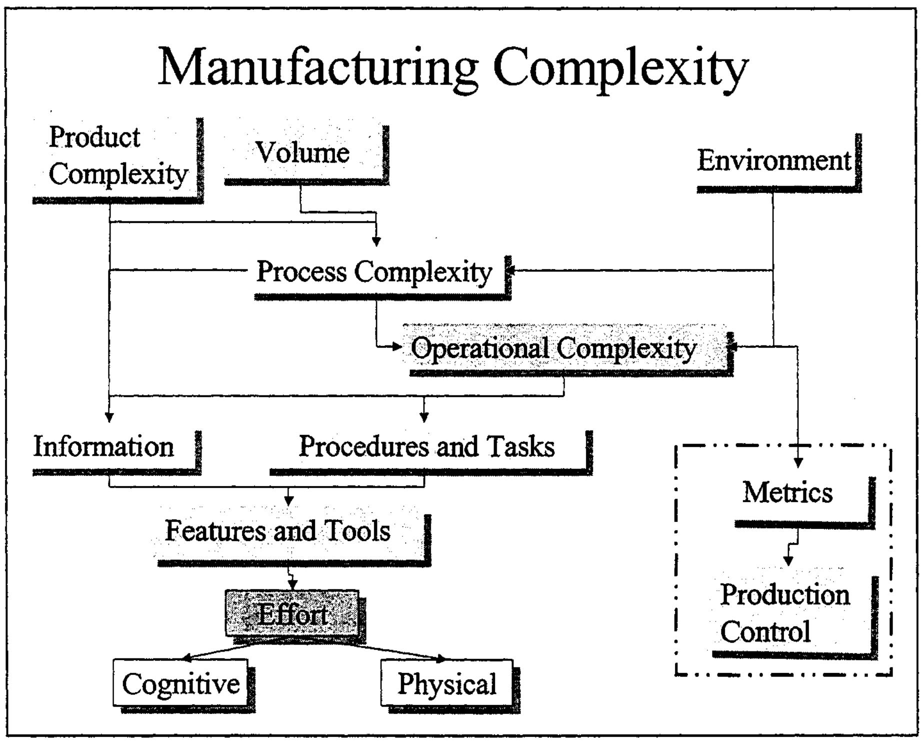


FIGURE 7.15: MANUFACTURING COMPLEXITY

7.4.1 Product Complexity

To start, it was assumed that product complexity could be divided into the main categories illustrated in Figure 7.16. The product complexity index $CI_{product}$ is defined to be a function of:

- the absolute number of features and specifications N
- the measure of the uniqueness of the features or the diversity ratio $D_{R\,product}$

- the manufacturing complexity or effort of the features based on general manufacturing principles $c_{j,product}$

$$CI_{product} = f(N, D_{R\,product}, c_{j,product}) \tag{7.9}$$

The quantity of information is a factor, but the "absolute quantity of information" may contain much redundancy. For example, the absolute quantity of information for the diameter of a six hole bolt pattern would be 18: 6 nominal values for diameter + 6 upper tolerance limits + 6 lower tolerance limits. However, only three pieces of information are relevant: 1 nominal diameter, 1 upper tolerance limit and 1 lower tolerance limit.

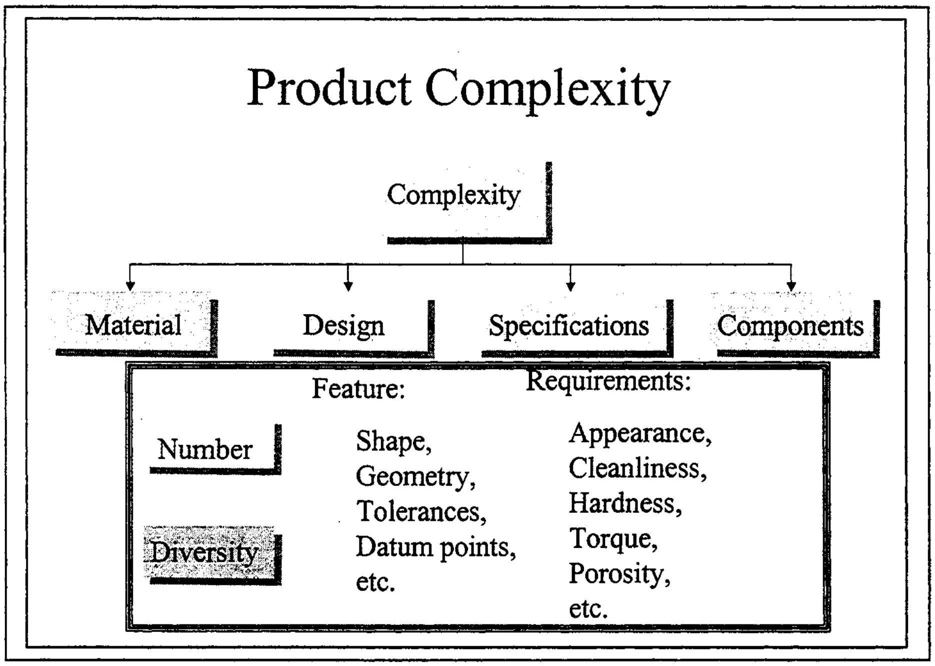


FIGURE 7.16: PRODUCT COMPLEXITY

Therefore a compression factor, the information entropy measure $H_{product}$ as expressed by equation 6.6, will be used to express the information quantity element:

$$H_{product} = \log_2(N+1) \tag{6.6}$$

where N is the total quantity of feature information.

The measure of uniqueness or the product diversity ratio $D_{Rproduct}$ will be defined as a ratio of distinct feature information to total feature information, as given by:

$$D_{Rproduct} = \frac{n}{N} \tag{7.10}$$

where n is the quantity of unique feature information and N is the total quantity of feature information.

The product manufacturing complexity coefficient $c_{j,product}$ is generally consistent with the earlier definitions, but has been slightly modified to distinguish between features and specifications (e.g. no burr or sharp edges on intersecting holes, cleanliness, hardness, etc.), and to include a percentage weighting factor:

$$c_{j,product} = \sum_{f=1}^{F} x_f * c_{f,feature} \tag{7.11}$$

where c_f is the relative complexity coefficient of the feature, sub-component, process, etc.

x_f is the percentage of the x^{th} dissimilar feature

$$c_{f,feature} = \frac{F_N * F_{CF} + S_N * S_{CF}}{F_N + S_N} \tag{7.12}$$

where F_N is the quantity of features

F_{CF} is the feature complexity factor

S_N is the quantity of specification checks

S_{CF} is the specification complexity factor

$$F_{CF} = \frac{\sum_{j=1}^{J} factor\_level_j}{J} \tag{7.6}$$

where F_{CF} is the feature complexity factor

J is the number of categories

factor_level$_j$ is the factor for the j^{th} category

$$S_{CF} = \frac{\sum_{k=1}^{K} factor\_level_k}{K} \tag{7.13}$$

where S_{CF} is the specification complexity factor

K is the number of specifications

factor_level$_k$ is the factor for the k^{th} specification

As with the analysis techniques introduced in section 7.3, a predetermined multi tier ranking system (e.g., low, medium, and high, which would correspond to a factor levels 0, 0.5 and 1 respectively, or a 1 – 10 scale, which is subsequently normalized) is used.

What form should these parameters take when representing a robust complexity measure? This needs to be investigated. Using utility curves, the relationship between the complex index CI is plotted with respect to the number of features N, the information content H, the diversity ratio $D_{R,\ product}$, and the complexity coefficient $c_{j,product}$ in Figures 7.17 – 7.20. Three formats were tested:

$$CI_{product} = D_{R_{product}} * c_{j,product} * H_{product} \tag{7.14 a}$$

$$CI_{product} = D_{R_{product}} + c_{j,product} + H_{product} \tag{7.14b}$$

$$CI_{product} = (D_{R_{product}} + c_{j,product}) * H_{product} \tag{7.14c}$$

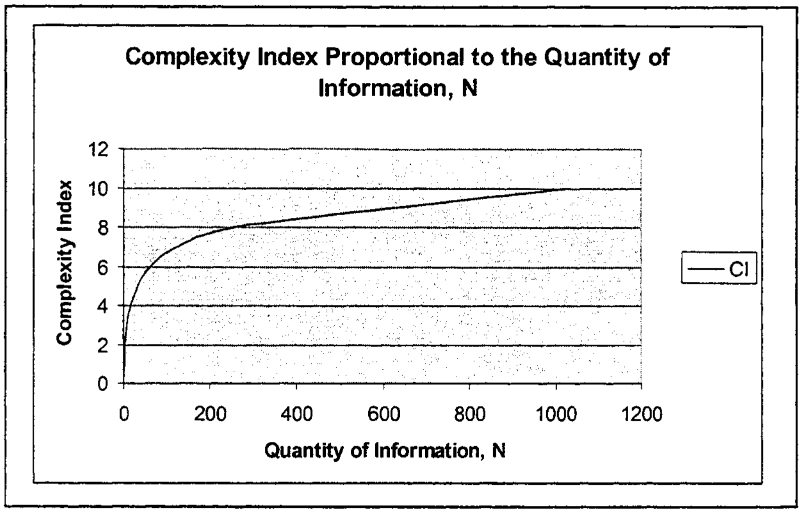


FIGURE 7.17: UTILITY CHART - THE CI ∝ QUANTITY OF INFORMATION, N

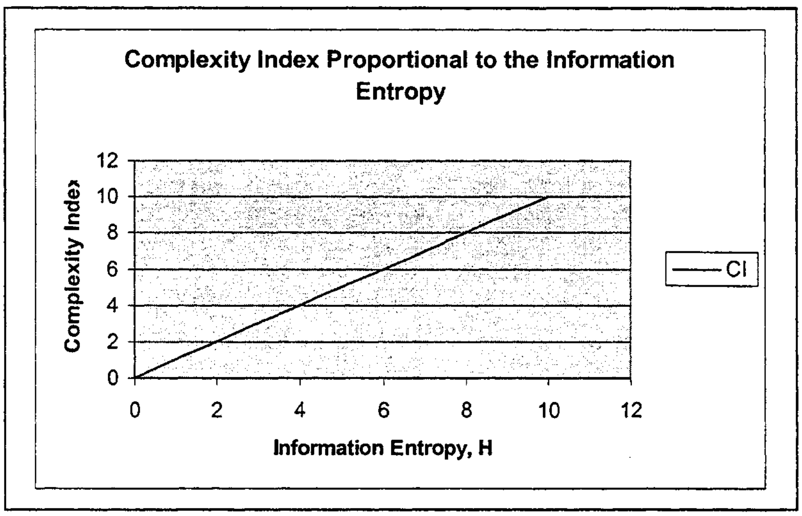


FIGURE 7.18: UTILITY CHART - THE CI ∝ INFORMATION ENTROPY, H

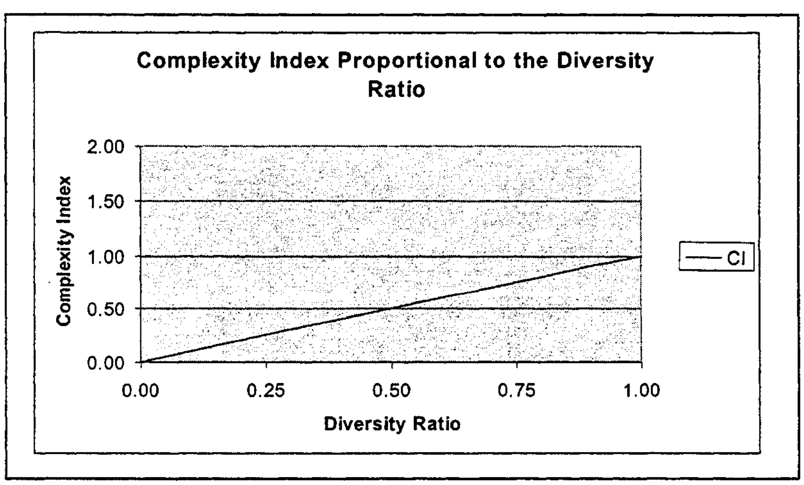


FIGURE 7.19: UTILITY CHART - THE CI ∝ THE DIVERSITY RATIO, D_R

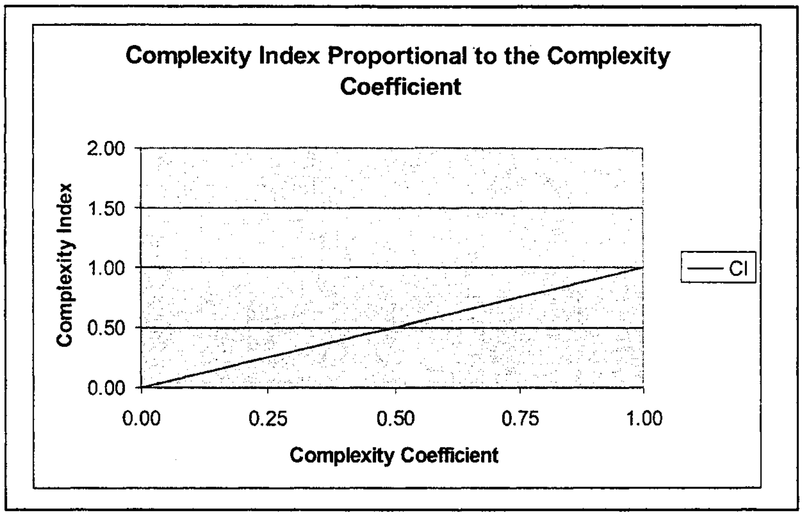


FIGURE 7.20: UTILITY CHART - THE CI $\propto$ THE COMPLEXITY COEFFICIENT

As the product diversity ratio $D_{Rproduct}$ and the product manufacturing complexity coefficient $c_{j,product} \rightarrow 1$, the more diverse and complex the product is. However, these measures by themselves are misleading when considering total complexity. A part with minimal, "simple" geometry but with extremely tight tolerances such as a cylinder bore sleeve would satisfy the above conditions, but the quantity of information is low. The tapped holes of a cylinder block represent the opposite end of the spectrum, the product diversity ratio $D_{Rproduct}$ and the product manufacturing complexity coefficient $c_{j,product} \rightarrow 0$, but the quantity of information is high. The complexity index must be relevant for all the extreme cases. Table 7.3 illustrates the extreme cases with the three potential formats.

When using equation 7.14a, if either the product diversity ratio $D_{Rproduct}$ or the product manufacturing complexity coefficient $c_{j,product} \rightarrow 0$, independent of the value of H, the complexity index CI is driven to zero. The opposite effect occurs with equation 7.14b. The value of $CI \rightarrow H$ as either the product diversity ratio $D_{Rproduct}$ or the product manufacturing complexity coefficient $c_{j,product} \rightarrow 0$, essentially inflating the value of the CI. Neither case is acceptable. Using the information entropy measure $H_{product}$ as a scaling factor as presented in equation 7.14c resolves these issues, and generates the most reasonable results.

	H = 1	H = 10	H = ∞
c_j=0 D_r=0	0	0	0
c_j=1 D_r=0	0	0	0
c_j=0 D_r=1	0	0	0
c_j=1 D_r=1	1	10	∞

$$CI_{product} = D_{R_{product}} + c_{j,product} + H_{product}$$

	H = 1	H = 10	H = ∞
c_j=0 D_r=0	1	10	∞
c_j=1 D_r=0	2	12	∞
c_j=0 D_r=1	2	12	∞
c_j=1 D_r=1	3	13	∞

$$CI_{product} = (D_{R_{product}} + c_{j,product}) * H_{product}$$

	H = 1	H = 10	H = ∞
c_j=0 D_r=0	0	0	0
c_j=1 D_r=0	1	10	∞
c_j=0 D_r=1	1	10	∞
c_j=1 D_r=1	2	20	∞

TABLE 7.3: EXPLORING POTENTIAL FORMATS FOR THE COMPLEXITY INDEX

Therefore, the product complexity index $CI_{product}$ is a combination of the diversity ratio and the relative complexity, and is scaled by its information entropy. This is expressed below as:

$$CI_{product} = (D_{R_{product}} + c_{j,product}) * H_{product} \text{ or} \qquad (7.14c)$$

$$CI_{product} = (\frac{n}{N} + c_{j,product}) * \log_2(N+1) \qquad (7.15)$$

The methodology is to generate the product complexity index $CI_{product}$ is developed below:

1) Define the multi-tier ranking system to be used for the analysis.

2) Determine the total number N of all the individual feature information, components, sub-components, etc. and from equation 6.5, calculate $H_{product}$.

3) Determine the specific quantity n of each diverse feature defined in step 2, and from equation 7.10 calculate the product diversity ratio $D_{Rproduct}$.

4) Define the number and type of diverse "aspects" for evaluating the features *(J)* and the specifications *(K)* associated with manufacturing the product.

5) Generate the *FxJ* feature matrix and the *FxK* specification matrix and assign the appropriate complexity levels into each cell.

6) Calculate the product complexity coefficient $c_{j,product}$ as defined by equations, 7.6 and 7.11 to 7.13.

7) Calculate the product complexity index $CI_{product}$ as defined by equation 7.15.

Let us consider a simple example: variations of a spacer plate with six drilled holes as illustrated in Figure 7.21. Spacer plates are typically unique, manually machined components that are used for precision alignment of machine elements such as fixtures or spindles. With all things considered equal (material, tolerances, etc.) it is obvious that 'E' is more complex than 'A'. Assume that the diameter and positional tolerances have a general manufacturing tolerance for a drilled hole, all the holes are through holes, and that the plate material is stock cold rolled steel, has been pre-machined to size, and needs to be ground to appropriate thickness.

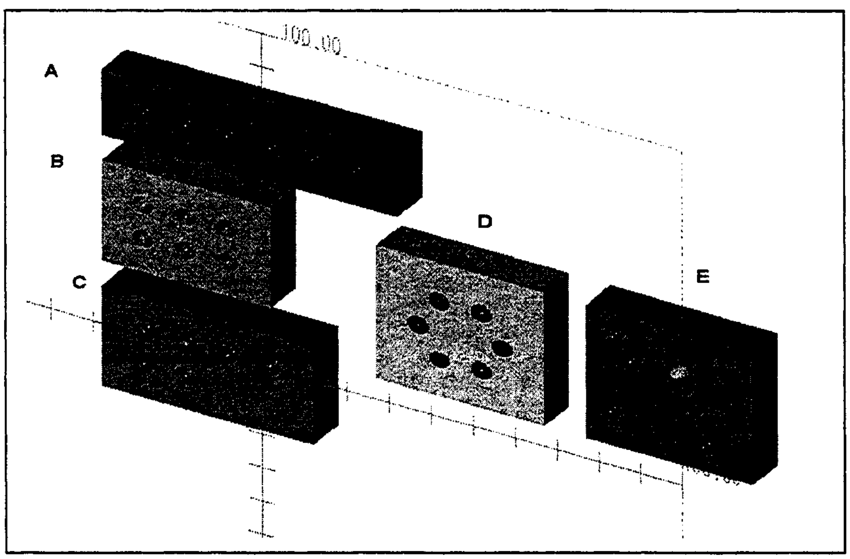


FIGURE 7.21: EXAMPLE – SPACER WITH 6 DRILLED HOLES

The features to be considered for each plate, the information quantity, diversity and manufacturing complexity are shown in Tables 7.4, 7.5 and 7.6. Note: analysing the plates using the method created in section 7.3 generated a product complexity coefficient $c_j \approx 0.0$ for all the cases.

Feature	Example				
	A	B	C	D	E
Length	1	1	1	1	1
Tolerance	1	1	1	1	1
Width	1	1	1	1	1
Tolerance	1	1	1	1	1
Thickness	1	1	1	1	1
Tolerance	1	1	1	1	1
Diameter	6	6	6	6	6
Tolerance	6	6	6	6	6
Depth	6	6	6	6	6
Tolerance	6	6	6	6	6
Position	1	1	1	1	1
Increment(s)	1	2	2	2	0
X values	6	6	6	6	6
Y values	6	6	6	6	6
Sum	**44**	**45**	**45**	**45**	**43**

TABLE 7.4: QUANTITY

Distinct Features	Example				
	A	B	C	D	E
Length	1	1	1	1	1
Tolerance	1	1	1	1	1
Width	1	1	1	1	1
Thickness	1	1	1	1	1
Height	1	1	1	1	1
Tolerance	1	1	1	1	1
Diameter	1	1	1	1	1
Tolerance	1	1	1	1	1
Depth	1	1	1	1	1
Tolerance	1	1	1	1	1
Position	1	1	1	1	1
Increment(s)	1	2	2	2	0
X values	6	3	4	4	6
Y values	1	2	2	3	6
Sum	**19**	**18**	**19**	**20**	**23**

TABLE 7.5: DIVERSITY

Description	Features J = 5							
	Number	**Aspects**						
		Material	**Shape**	**Geometry**	**In-process steps**	**Tolerances**	**SUM**	**Sum/J**
Plate Length	1	0	0	0	0	0	0	0
Plate Width	1	0	0	0	0	0	0	0
Plate Thickness	1	0	0	0	0	0.5	0.5	0.1
Hole diameter	6	0	0	0	0	0	0	0
Hole depth	6	0	0	0	0	0	0	0
Hole position	6	0	0	0	0	0	0	0
Product Complexity Coefficient					c_j=	0.029		

TABLE 7.6: COMPLEXITY

Using equation 7.15, the product complexity index for ‘A’ to ‘E’ is summarized in Table 7.7.

	A	B	C	D	E
H: Information Entropy	5.46	5.49	5.49	5.49	5.43
D_R: Diversity Ratio	0.43	0.40	0.42	0.44	0.53
$c_{j,product}$	0.03	0.03	0.03	0.03	0.03
$CI_{product}$	2.51	2.35	2.48	2.60	3.06

TABLE 7.7: SUMMARY

As expected, ‘E’ is the most complex product. Product designs ‘A’ to ‘D’ are clustered, with ‘D’ being the most complex. ‘C’ and ‘A’ are almost equivalent and ‘B’ is the least complex. Although this may not be intuitive, more information is required to manufacture and measure product ‘A’ versus products ‘B’ and ‘C’ – independent of the manufacturing process.

7.4.2 Process Complexity

The process complexity, illustrated in Figure 7.22, is a function of the product design, the volume requirements and planning horizon, and the work environment. All inputs influence the process design and layout, equipment specifications and so forth. The main constituents of the manufacturing process must be identified to generate the process complexity index *PI*, as each constituent is a factor of process complexity. The examples in this document will focus on machining, but the framework can be extended into any environment.

In the machining environment, a sample of the process complexity constituents follows:

- in-process features and steps,
- types of tools, tool holders, spindles,
- fixtures or set-ups, product orientations,

- type of machines,
- type of gauges to measure individual features and feature relationships,
- material handling, and so forth.

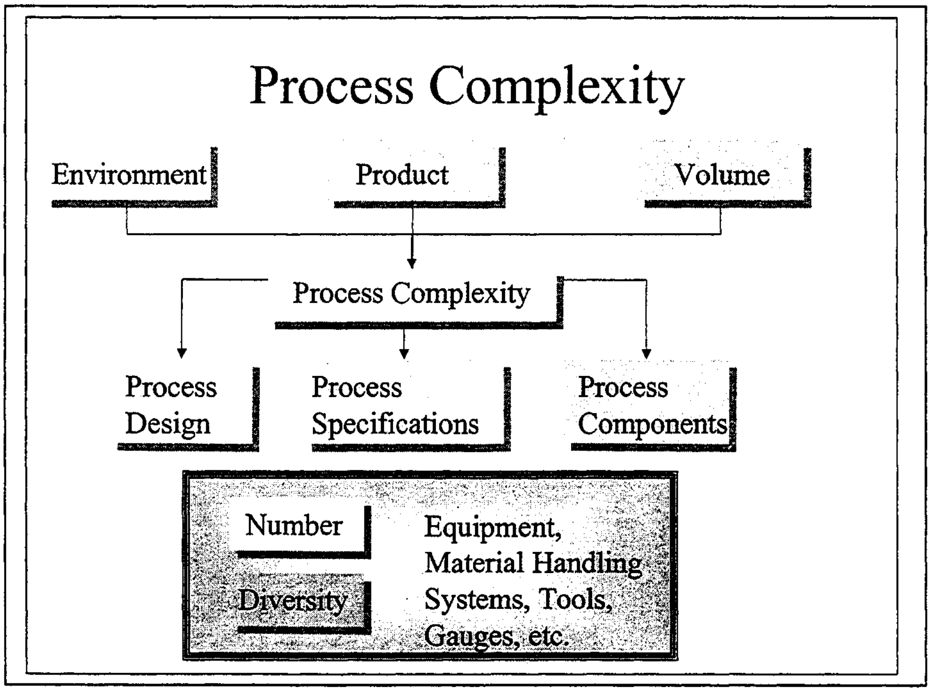


FIGURE 7.22: PROCESS COMPLEXITY

Although there are many facets to process complexity, the methodology that was established to generate a product complexity measure can be extended to embrace these different elements.

First, all the relevant constituents to be used in the analysis must be identified (e.g. Table 7.8). Then the quantity and diversity of information for each constituent must be tabulated.

Complementing the product complexity analysis, the information entropy of each constituent x is:

$$H_{process,x} = \log_2(N_{process,x} + 1) \tag{7.16}$$

where $N_{process,\,x}$ is the total quantity of information for the x^{th} constituent being considered.

	Total	Distinct	$D_{Rconstituent}$
Fixtures			
Tools			
Gauges			
Machines			
In-process Features			
In-process Specifications			
Product Features			
Product Specifications			

Physical Process Elements

Produced Geometry

Product Complexity

TABLE 7.8: PROCESS FACTORS

The diversity ratio $D_{R\ process,x}$ for the x^{th} individual process constituent is defined as:

$$D_{R\ process,x} = \frac{n_{process,x}}{N_{process,x}} \tag{7.17}$$

where $n_{process,\,x}$ is the quantity of unique feature information for the x^{th} individual process constituent being considered, and

$N_{process,\,x}$ is the total quantity of feature information for the x^{th} individual process.

For the j^{th} constituent, the complexity coefficient $c_{process,j}$ is defined as:

$$c_{process,j} = \sum_{f=1}^{F} x_f * c_{process,fsubfeature} \tag{7.18}$$

where $c_{process,\,fsubfeature}$ is the relative complexity coefficient of the feature, sub-component, process, etc., and when comparing to equation 7.5, here:

$$c_{process,\,fsubfeature} = Fc_{CF}$$

Fc_{CF} is the feature complexity factor (Note: if there are specifications that need to be taken into account, the direct format from equation 7.5 should be used).

x_f is the percentage of the x^{th} dissimilar feature

$$Fc_{CF} = \frac{\sum_{j=1}^{J} factor\_level_j}{J} \tag{7.19}$$

where Fc_{CF} is the feature diversity factor

J is the number of evaluation factors

$factor\_level_j$ is the factor for the j^{th} evaluation factor

The x^{th} individual process constituent complexity index pc_x is:

$$pc_x = (D_{R\,process,x} + c_{process,x}) * H_{process,x} \tag{7.20}$$

The process complexity index is the sum of the individual constituent complexity values and the product complexity, and is expressed as:

$$PI_{process} = \sum pc_x + CI_{product} \tag{7.21}$$

At both the micro and macro level, the process complexity measures are very rich in information. As $D_{R\ process,\ x}$ and $c_{\ process,\ x} \rightarrow 1$ and $H_{\ process,\ x} \rightarrow \infty$ for any factor, and as PI increases, the difficulty to "manage" that factor or process (such as the ability to train, troubleshoot, and perform maintenance) also increases. This is especially true if unique, unproven, or non-standard designs are used for the various constituents, which is typical when launching a new product and process. The matrix methodology used to define the process manufacturing complexity coefficient has been extended to evaluate the complexity of the individual constituents; however, for analysis purposes $c_{\ process,\ x}$ is assumed to be zero, as this level of detail is beyond the scope of this research.

An example for generating process complexity index is presented for a die-cast aluminum (10% Si. max) power steering pump bracket (Figure 7.6). This product had migrated from a flexible CNC work cell process to a dedicated machine work cell. Both process complexity indices are computed and compared. The required volumes of this product had increased by a significant factor, and it became cost inefficient utilizing a CNC machine based process. The product complexity information is presented in Appendix C. The process complexity and the sub-elements are presented in Table 7.9.

The fixture, machine and spindle diversity ratios are greater for the dedicated equipment as compared to the CNC equipment. Typical for dedicated equipment, the machines, fixtures and spindles/heads were designed for a specific application; hence, these results are expected. Conversely, there is less diversity in the tooling, as dedicated machines generate several identical features simultaneously, whereas flexible machines manufacture features serially. In general, the following should hold true when comparing dedicated versus flexible equipment:

$$D_{Rfixture}\, DMS > D_{Rfixture}\, CNC \tag{7.22}$$

$$D_{Rspindle}\, DMS > D_{Rspindle}\, CNC \tag{7.23}$$

$$D_{Rmachine}\, DMS > D_{Rmachine}\, CNC \tag{7.24}$$

$$D_{Rtool}\, DMS < D_{Rtool}\, CNC \tag{7.25}$$

The dedicated machine work cell process is approximately 25% more complex than the flexible CNC process. If other factors such as tool holders and programmable controllers were included, the process complexity index for dedicated equipment would continue to increase as compared to the CNC based process. This has several repercussions with respect to troubleshooting, training, maintenance and procurement of spare parts.

CNC process + Bushing Machine						1 CNC + 4 Dedicated Machines Work Cell					
	Total	H	Distinct	D_{Rx}	pc_x		Total	H	Distinct	D_{Rx}	pc_x
Fixtures	13	3.81	2	0.154	0.586	Fixtures	8	3.17	5	0.625	1.981
Tools	20	4.39	19	0.950	4.173	Tools	26	4.75	19	0.731	3.475
Spindles/ Head/ Lead screws	2	1.58	1	0.500	0.792	Spindles/ Head/ Lead screws	14	3.91	14	1.000	3.907
Gauges - hand	30	4.95	30	1.000	4.954	Gauges - hand	30	4.95	30	1.000	4.954
Gauges - relation	2	1.58	2	1.000	1.585	Gauges - relation	2	1.58	2	1.000	1.585
Machines	3	2.00	2	0.667	1.333	Machines	5	2.58	5	1.000	2.585
In-process Features	42	5.43	27	0.643	3.488	In-process Features	42	5.43	27	0.643	3.488
SUM					16.912	SUM					21.975
$CI_{product}$	79	6.32	47	0.595	4.424	$CI_{product}$	79	6.32	47	0.595	4.424
$c_{i,product}$					0.105	$c_{i,product}$					0.105
Process Complexity					21.336	Process Complexity					26.399

TABLE 7.9: PROCESS COMPLEXITY COMPARISON FOR STEERING BRACKET

A chart comparing the individual constituent complexity is shown in Figure 7.23. From this, it is can be ascertained that the tools and the hand gauges have significantly higher measures than the machine measure. But what does this mean? It means that it will take longer for people to learn about the gauges and tools as compared to familiarizing themselves with the machines. It must be noted that a more in-depth information content analysis should be performed for each constituent (i.e. the fixture information content should be extended to include the locating datum, and the type and quantity of part touching details and supports, and so forth). However upon performing a first level analysis, the general trends can be established.

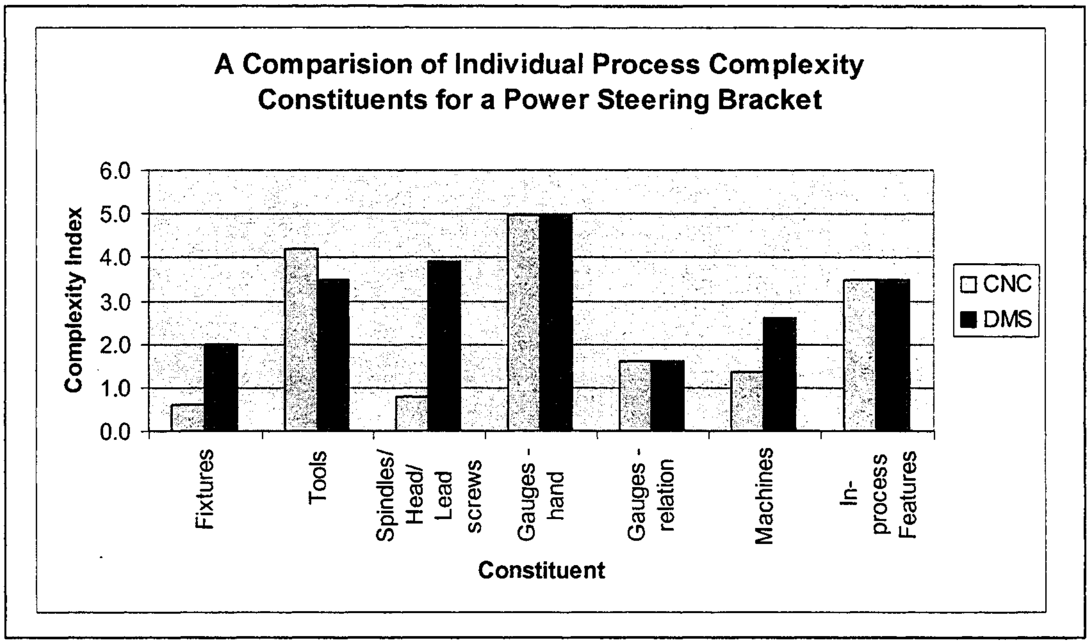


FIGURE 7.23: PROCESS COMPLEXITY FACTORS

7.4.3 Operational Complexity

The operational complexity is a function of the product, process, volume requirements and the work environment, as illustrated in Figure 7.24.

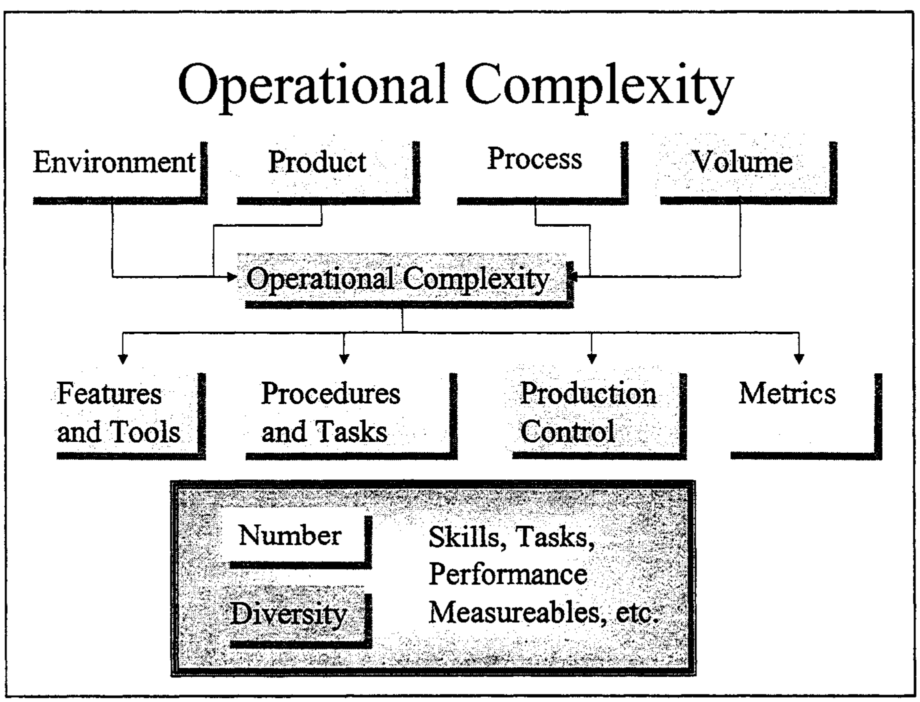


FIGURE 7.24: OPERATIONAL COMPLEXITY

For this research, the focus of the operational complexity is on the information and tasks associated with manufacturing the product, not the scheduling and routing or other production control elements. The depth of the analysis is dependent upon its scope: the analysis can be performed for the complete process or a subset of the process such as a work cell, or operations assigned to an operator.

The information and skill sets required to perform the tasks are either product related (focus is on quality related aspects) or process related (focus is on machine operation, throughput or efficiency), illustrated in Figure 7.25. The product related tasks directly correspond to the in-process or final product requirements: gauging, changing the tools, adjusting equipment for quality purposes, etc. The process related tasks correspond to the manufacturing process: process related set-ups, pre-assembly, running the equipment, proper equipment safety lockout, process fault analysis, material handling, etc. Analysis can be performed for the operators, technical support or management. The framework is consistent: the individual components used in the analysis would vary.

The determination of the operational complexity index *OI* is consistent with the previous measures. For the operational complexity measure there are two constituents to be considered: the product and process.

The information entropy of each constituent y is:

$$H_{op,y} = \log_2(N_{op,y} + 1) \tag{7.15}$$

where $N_{op,y}$ is the total quantity of either the product and process related elements respectively.

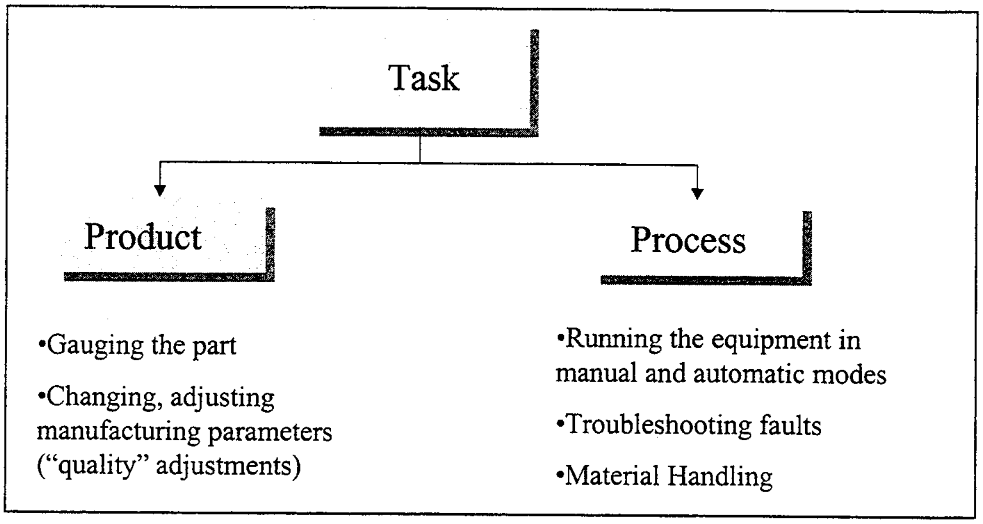


FIGURE 7.25: TASK BREAKDOWN

The diversity ratio $D_{R\ op,y}$ for each individual operational constituent is defined as:

$$D_{R\,op,y} = \frac{n_{op,y}}{N_{op,y}} \tag{7.16}$$

where $n_{op,y}$ is the quantity of unique tasks for the product or process constituents, and

$N_{op,y}$ is the total quantity of product or process tasks.

The operation based complexity coefficient is defined differently as effort plays a factor, and for the sake of clarity will be called the relative operational complexity coefficient c_o.

7.4.3.1 Relative Effort Index

Skills, effort and complexity are interlinked. For the purposes of this research, "effort" will be considered separately from "complexity". Effort and complexity are related but not equivalent. A complex task may be broken into several simple (effortless) subtasks; consequently, effort can be thought of as a subset of complexity. A simple example illustrates this.

Consider a part that has four step-drilled holes, as shown in Figure 7.26. For each hole, the depth, diameter, and chamfer depth must be measured to determine whether they are within specification; hence, twelve checks need to be performed. There are two standard methods of gauging these features: (1) using a dial caliper or (2) using plug gauges.

A multi-step procedure is necessary when using a dial caliper. The steps, and the time taken to execute the steps, are listed below:

- measure, which takes time t_{mv},
- read the gauge, which takes time t_r,
- compare to specification, which takes time t_s and
- make a decision, , which takes time t_d.

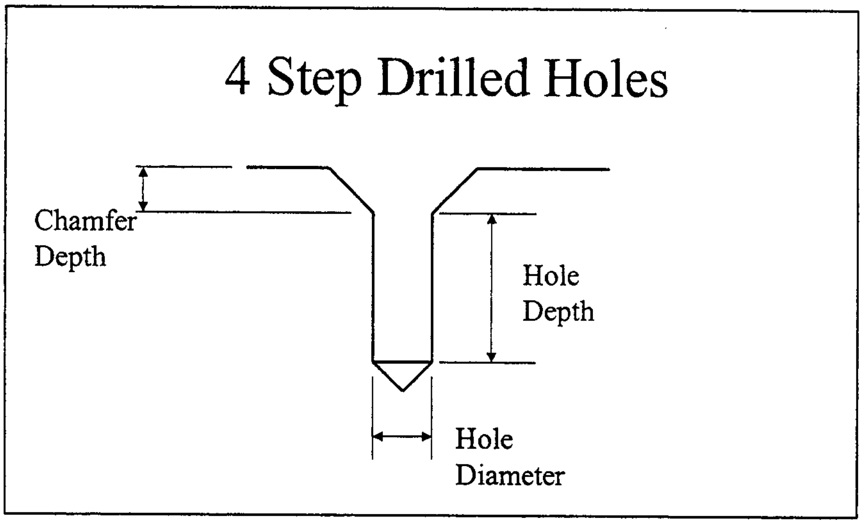


FIGURE 7.26: STANDARD TAP DRILL HOLE

Using a format analogous to the Model Human Processor described in chapter 6, the time to measure the part is:

$$t_{gauge_{dial}} = (t_{mv} + t_r + t_s + t_d) * 12 \quad \{3 \text{ features} * 4 \text{ holes}\} \tag{7.26}$$

Reading the dial caliper has both a cognitive and perceptual time element (t_{c_r} and t_{p_r}); and comparing the measurement to the specification has a cognitive time element t_{c_s}. There two decision choices: (1) determine whether the part is good or bad, and (2) remeasure.

Using the equations for uncertainty (6.5 and 6.6) and the Model Human Processor (equation 6.9), the time to gauge these features can be represented by:

$$t_{gauge\ dial} = (t_{mv} + t_{c_r} + t_{p_r} + t_{c_s} + I_c \log_2(n+1)) * 12 \tag{7.27}$$

Assume $t_{c_r} = t_{c_s}$ and $n=2$. Equation (7.27) reduces to:

$$t_{gauge\ dial} = (t_{mv} + 2t_{c_r} + t_{p_r} + 1.6I_c) * 12 \tag{7.28}$$

For using a plug gauge the steps, and the time taken to execute the steps, are listed below:

- insert (t_{m_plug}).

The time to gauge the features using a plug gage is represented by:

$$t_{gauge\ plug} = t_{m-plug} * 12 \tag{7.29}$$

where $t_{m-plug} << t_{mv}$.

Using t_{mv} = 6 sec, t_{c_r} = 70 msec, t_{p_r} =100 msec, I_c = 150 msec, and t_{m-plug} = 1.5 sec

$t_{gauge\ dial}$ = 78 sec and $t_{gauge\ plug}$ =18 sec.

Table 7.10 contains a summary of the above example.

GAUGE METHOD	PHYSICAL SKILL REQ'D	COGNITIVE SKILL REQ'D	DECISION MAKING REQ'D	TIME TO GAUGE	SKILL LEVEL	GAUGE COST
Dial Caliper	Yes	Yes	Yes	~ 80 sec.	Technician	~\$100 - \$200
Plug Gauges	None	None	None	~ 20 sec.	Illiterate	~\$900 - \$1300

TABLE 7.10: EFFORT VERSUS GAUGING METHOD

Essentially, using plug gauges allows an unskilled person to quickly verify features in a part. Note that there is a cost penalty using plug gauges. The simplest plug gauge costs approximately twice as much as a standard dial caliper gauge.

The process of reducing complexity into simple elements is the foundation for dedicated manufacturing systems and the "tall" pyramid organizational structure as discussed in previous chapters. As well, a simple task should not be considered complex if the employee does not have the skills and experience in order to be able to effectively perform the task. The task remains simple, but requires much more individual effort on the part of the employee. Therefore, effort can be considered a function of physical or cognitive labour. The immediate environment will also influence the physical effort: for example, high temperatures and humidity are definite influences. This is shown in Figure 7.27.

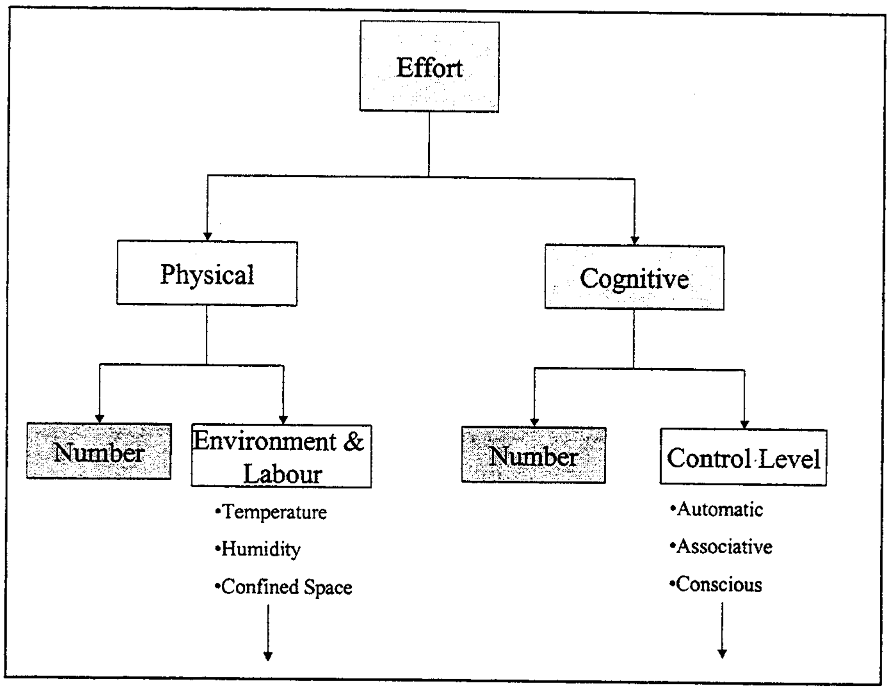


FIGURE 7.27: EFFORT HIERARCHY

Various process or product related tasks are required to be performed in order to generate specific features. As shown in Figure 7.28, J tasks are related to the i^{th} feature. For each cell ($i_{feature}$ x j_{task}), there is an associated effort. In lieu of assigning general rankings, a detailed effort analysis is performed which considers physical and cognitive elements as a subset of the operational complexity coefficient.

	Tasks J = 4						
	Number	Product Skills					
		Setup Tools	Change Tools	Relation Gauge Features	Hand Gauge Features	SUM	D/J
Tapped holes	16	0.30	0.33	0.08	0.13	0.84	0.21
Drilled holes	24	0.30	0.50	0.25	0.25	1.30	0.33
Bored holes	8	0.52	0.48	0.33	0.33	1.66	0.42
Milled surfaces	8	0.22	0.37	0.25	0.08	0.92	0.23
Assembly	4	0	0.37	0	0.08	0.45	0.23

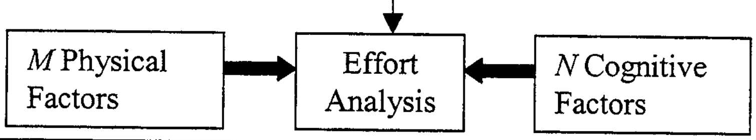


FIGURE 7.28: RELATIONSHIP BETWEEN FEATURES, TASKS AND EFFORT

To start, the relative operational complexity coefficient c_o is defined as:

$$c_{o,product} = \sum_{f=1}^{F_{PD}} x_{pd,f} * Pd_D \qquad (7.30)$$

$$c_{o,process} = \sum_{f=1}^{F_{PC}} x_{pc,f} * Pc_D \qquad (7.31)$$

where $x_{pd,f}$ is the percentage of the x^{th} dissimilar feature or feature groups used in the analysis

Pd_D is the task complexity factor

$x_{pc,f}$ is the percentage of the x^{th} dissimilar features for process related tasks

Pc_D is the process complexity factor

$$Pd_D = \frac{\sum_{j=1}^{J} e_{f_j}}{J} \qquad (7.32)$$

where Pd_D is the product task complexity factor

J is the number of product tasks

e_{fj} is the effort factor e_f for the j^{th} product task as defined by the relative effort (next section)

$$Pc_D = \frac{\sum_{k=1}^{K} e_{f_k}}{K} \tag{7.33}$$

where Pc_D is the process task complexity factor

K is the number of process tasks

e_{fk} is the effort factor e_f for the k^{th} process task as defined by the relative effort (next section)

The relative effort index e_f is defined as:

$$e_f = \frac{P_N * P_D + C_N * C_D}{P_N + C_N} \tag{7.34}$$

where P_N is the quantity of physical tasks

P_D is the physical effort factor

C_N is the quantity of cognitive tasks

C_D is the cognitive effort factor

$$P_D = \frac{\sum_{m=1}^{M} factor\_level_m}{M} \tag{7.35}$$

where P_D is the physical effort factor

M is the number of physical components

$factor\_level_m$ is the factor for the m^{th} feature

$$C_D = \frac{\sum_{n=1}^{N} factor\_level_n}{N} \tag{7.36}$$

where C_D is the cognitive effort factor

K is the number of cognitive tasks

$factor\_level_n$ is the factor for the n^{th} task

The multi tier ranking system used for effort needs to be considered for two scenarios:

(1) the first is a reflection of the environment (e.g., no discomfort or effect, moderate discomfort or effect, and high discomfort or effect, which would correspond to a factor levels 0, 0.5 and 1 respectively, or a 1 –10 scale) and

(2) the control level for both the physical and cognitive work (e.g., automatic, associative and conscious → 0, 0.5 and 1).

In lieu of a generic ranking system, a more thorough analysis similar to the Model Human Processor could be used for a detailed perspective of any task. Further work should be performed in this area, as there are cost, quality and productivity repercussions that would be highlighted in an objective manner.

After the ranking system is defined, the following steps are used to determine the effort index.

1) Define the F_{PD} product related features, the J product related tasks, the F_{PC} process related features and the K process related tasks to be performed.

2) Determine the number of features and tasks defined in step 1.

3) Define the type of physical *(M)* and cognitive *(N)* "aspects".

4) Generate the $F_{PD}xJ$ and $F_{PC}xK$ product and process matrices.

5) General physical effort matrices and the JxM and JxN cognitive effort matrices for the product related effort analysis, and assign the appropriate effort levels into each cell, as shown in Appendix D.

6) General physical effort matrices and the *KxM* and *KxN* cognitive effort matrices for the process related effort analysis, and assign the appropriate effort levels into each cell, as shown in Appendix D

7) Calculate the relative effort coefficient e_f as defined by equations 7.34 to 7.36.

Upon determining the effort index for each task, these values are used to determine the operational complexity measure.

8) Substitute the values of the relative effort coefficient e_f as appropriate into equations 7.30 to 7.33 and calculate the relative operational complexity coefficient $c_{o,product}$ and $c_{o,\ process}$.

The operational complexity index is defined as:

$$OI = (D_{Rop,product} + c_{o,product}) * H_{op,product} + (D_{Rop,process} + c_{o,process}) * H_{op,process} \tag{7.37}$$

Although the operational complexity is downstream from the product and process complexity, the operational complexity measure does not have a directly additive relationship with the product and process complexity measures. In essence, the operational complexity measure has gone through a transformation via "relative effort". The product and process information has been condensed and simplified. Based on the product and the required volumes, process flow, equipment, and fixture and tooling decisions have been made so that production operations are streamlined, hence the various disciplines and the areas of expertise in different departments. *The operational complexity index is the measurable that needs to be used in a human performance model.* The utility charts for diversity ratio, operational complexity, effort and information content and "practice" or experience are illustrated in Appendix E.

The relationship between effort and complexity can be developed one step further. The relative effort index changes with skill and experience. As the number of repetitions or the amount of practice increases, conscious effort becomes automatic. Hence this model could be used to correlate the effects of training and experience within the workforce to any process.

The total system complexity index, CI_{system} can be determined by summing the various indices: $CI_{system} = CI_{product} + PI + OI$ (7.38)

This is relevant when comparing the various process and operational options. For a given feature, there are several methods to produce it, each with an associated process complexity. Along with the production methods, there are several different procedures or tasks that are related to a given process, each with its operational complexity. This generates a tree structure of various complexity indices and is illustrated in Figure 7.29.

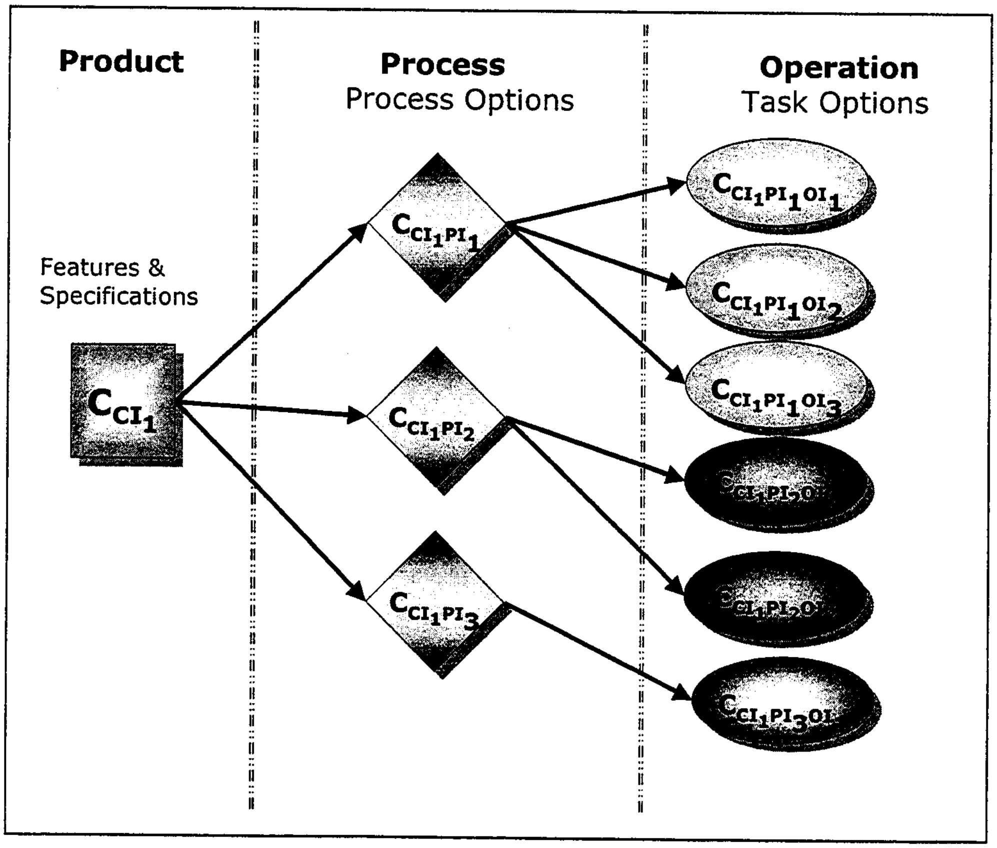


FIGURE 7.29: THE MANUFACTURING COMPLEXITY HIERARCHICAL RELATIONSHIPS

The total system complexity index, CI_{system}, is a value that is generated by considering all aspects of manufacturing complexity in a clear, concise, unbiased way.

7.4.4 Complexity Index Summary

To summarize, the simple, volume weighted product complexity index defined by Cooper et al [1992] could not be directly used. The index needed to be refined, and a systematic method for determining the complexity coefficient introduced. The framework and methods developed in this research can be applied to distinctly different environments.

Initially, product complexity was considered functions of the process and the related tasks. This expanded to include information and effort factors, and lead to the product complexity coefficient defined as:

$$c_f = \frac{X_{1,N} * X_{1,D} + X_{2,N} * X_{2,D} + X_{3,N} * X_{3,D} \ldots X_{M,N} * X_{M,D}}{X_{1,N} + X_{2,N} + \ldots X_{M,N}} \tag{7.8}$$

Although this coefficient provided good insight into relative complexity, upon performing an analysis on the sample products, some issues arose. When creating relevant matrix elements, several rows had a value of zero, which drove the complexity coefficient towards zero, essentially attenuating the values. A distinction needed to be made for product, process and operational elements of complexity, as the volume requirements and the work environment are direct influences. Very intricate parts with tight tolerances are made in high volumes with unskilled labour. Somehow the product complexity is transformed. This needed to be captured, and has been done in this research.

With this in mind, a new perspective was required and fresh assumptions were made. First, it was assumed that basic elements of complexity consisted of three factors: the quantity of information, the diversity of information and the information content. Secondly, there are three aspects of manufacturing complexity: the product, process and operational complexity. The product complexity is a function of the material, features, shape, geometry and tolerances, and so forth, and any special specifications such as no burrs, cleanliness, hardness, porosity, etc. The product complexity measure is expressed as:

$$CI_{product} = (D_{R_{product}} + c_{j,product}) * H_{product} \tag{7.14}$$

The process complexity measure is a function of the product, the volume requirements and the work environment. Each critical process factor or constituent must be identified, and its complexity measure is analyzed individually. The process complexity measure is a summation of the individual complexity measures, and includes the product complexity measure:

$$PI = \sum pc_x + CI_{product} \tag{7.21}$$

The operational complexity measure is a function of the necessary tasks that need to be performed within a given process to produce a given product, and the task effort. The tasks are either process or product related. There are two elements of effort: physical and cognitive, and the framework used to analyze effort must be able to reflect both aspects. The three factors of complexity (amount of information, diversity of information, and information content) are still the foundation of the operational complexity measure, but transformation has occurred, which is reflected in the relative effort analysis. Mistake proofing techniques, visual aids, colour coding, tool assists, ergonomic lift tables and other techniques are used to reduce both physical and cognitive effort, and consequently, the operational complexity measure. Conversely, there are some negative aspects to reducing complexity: cost is one of them. As complexity is reduced, costs increase, as in the example of the measuring holes with a dial caliper versus plug gauges. Another negative aspect is that information content is reduced. Again, in the example of using a dial caliper versus plug gauges, an operator who uses plug gauges can only determine whether the feature is "good" or "bad". There is no quantitative or historical information captured. The operational complexity measure is:

$$OI = (D_{Rop,product} + c_{o,product}) * H_{op,product} + (D_{Rop,process} + c_{o,process}) * H_{op,process} \tag{7.37}$$

The tasks identified in the operational complexity measure require certain skills that the workforce must have. The skills analysis is performed in the next section.

The total system complexity consists of the summation of all the individual indices and is:

$$CI_{system} = CI_{product} + PI + OI \tag{7.38}$$

This illustrates the coupling of feature, process and task complexity (that is typical within surveys which are utilized to define complexity), as well as the effects of tradeoffs between process and operational complexity and the influence of changing a feature tolerance or specification.

7.5 Skills Set Elements, Footprints, Matrices and Indices

There are two general categories for skills that are necessary to perform the tasks defined in the operational complexity index: personal skills and professional skills, as illustrated in Figure 7.30. Even if employees have all the relevant skills, experience and training, there is still a learning curve when exposed to a new situation (either product or process). But what if all skills are not present? A measure needs to be defined that indicates the novelty of the situation for an employee, and the skills mix or the amount of variation of skills within a work group.

This can readily be achieved by manipulating the skill novelty index and heterogeneity proposed by Reuer et al [2002+].

Skills

- Personal
- Physical
  - *Perceptual(Sensory inputs)*
  - *Vision*
  - *Hearing*
  - *Health*
  - *Motor outputs*
    - *→Reach, Dexterity*
- Cognitive
  - *Memory*
  - *Problem solving*
  - *Workload/Task/Stress Management*

- Professional
- Physical & Cognitive
  - *Specific Training*
  - *Education*
  - *Experience (similar products/processes/technology ...)*

FIGURE 7.30: SKILLS

Recall from chapter 5 Reuer et al [2002+] investigated skill novelty and heterogeneity for international joint ventures to determine the influence of skill and experience on the success of an international joint venture. They analyzed each industry's skill requirements in order to calculate these measures. Skill novelty is defined as the difference between needed skills and actual skills. Skill heterogeneity is the measure of diversity of the firm's previous experience. From Reuer et al [2002+]:

$$Skill\_Novely = \frac{1}{N} \bullet \sum_{j=1}^{N} [\sum_{i=1}^{I} \sqrt{\frac{(P_{ij} - P_{if})^2}{s_i^2}}] \tag{5.5}$$

where N is the number of joint ventures in the firm's experience base

I is the number of occupational divisions

P_{ij} is the percentage of employees in occupational division i for joint venture j's industry

P_{if} is the percentage of employees in occupational division i for the focal joint venture f

s_i^2 is the sample variance of employment percentages in occupational division i across all industries, which is used as a weighting factor.

$$Skill\_Heterogeneity = \sqrt{[\frac{1}{I} \sum_{i=1}^{I} \frac{v_i^2}{s_i^2}]} \tag{5.6}$$

where I is the number of occupational divisions

v_j is the sample variance in employment in occupational division i across the industries in which the firm has joint venture experience (i.e., $j \in J$).

P_{if} is the percentage of employees in occupational division i for the focal joint venture f

s_i^2 is the sample variance of employment percentages in occupational division i across all industries, which is used as a weighting factor.

To use these measures, first, a "skills" matrix composed of skills (rows) and employees (columns) must be developed (Figure 7.31a). Next, the skill novelty index S_N and the skill heterogeneity index S_H is reworked to reflect the manufacturing requirements:

$$S_N = \frac{1}{N} \bullet \sum_{n=1}^{N} [\frac{1}{I} \sum_{i=1}^{I} \sqrt{(\Delta P_{ij})^2}\,] \qquad (7.33)$$

where N is the number of skills for work cells, shifts or departments

I is the number of skills

ΔP_{ij} is the difference of the percentage of employees j whom **require** i

$$S_H = \frac{1}{N} \bullet \sum_{n=1}^{N} [\sum_{i=1}^{I} \sqrt{\frac{I\sum x_i^2 - (\sum x_i)^2}{I(I-1)}}\,] \qquad (7.34)$$

where N is the number of work cells, shifts or departments

I is the number of skills

x_i is the percentage of employees j that have skill i

The novelty index reflects the "newness" of the skill sets, training or tasks required to perform the functions defined in the operational complexity indices for an employee or team. The heterogeneity index reflects the amount of variation of skill levels between the employees.

In the example shown in Figure 7.31a, a binary or "yes-no" approach was taken when analyzing the indices. Another approach would be to add weighted values when calculating the indices. Either approach is valid, but the approach must be consistent throughout the analysis.

In order to visualize the "footprint" of employees and an organization represented by an "*Employee x Skills*" matrix, a radar chart as illustrated in Figure 7.31b is used. Each axis represents a unique skill; the centre is "0", the periphery is the maximum level. This graphical tool presents a quick visual snapshot of the status quo, and the necessary direction of growth. The boundaries defining low, medium and high skill sets must be determined. The effects of these levels on complexity and diversity on productivity are explored using utility charts in Appendix E, illustrating the influence of high, medium and low skill sets.

Ideally, the values of S_N and S_H would equal zero – this indicates that all employees have all necessary skill sets; there are no exceptions. In general terms, as $S_N \rightarrow 1$, the more unskilled the employees are; however, there is ambiguity with this measure. Almost identical values are derived by having a small group of employees with all the skills versus a small amount of skills acquired by all employees (Figures 32a and b). This is resolved by the skill heterogeneity index.

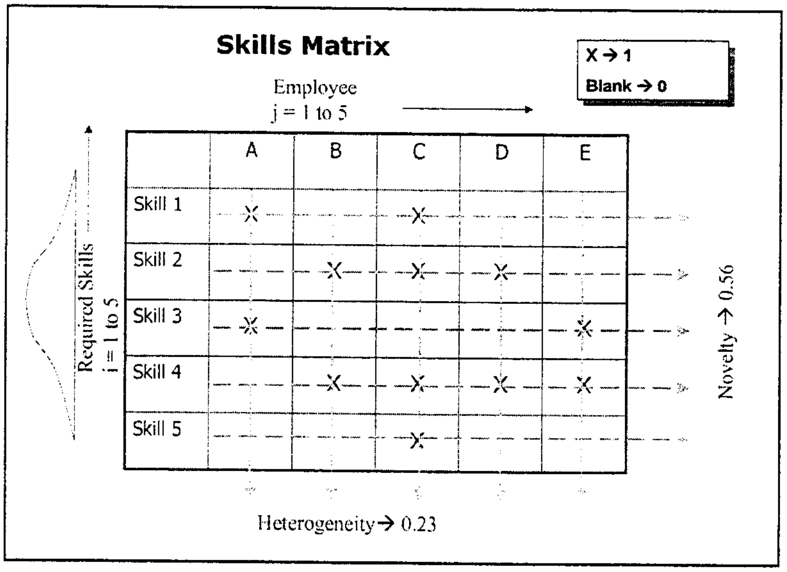


FIGURE 7.31A: SAMPLE SKILLS MATRIX

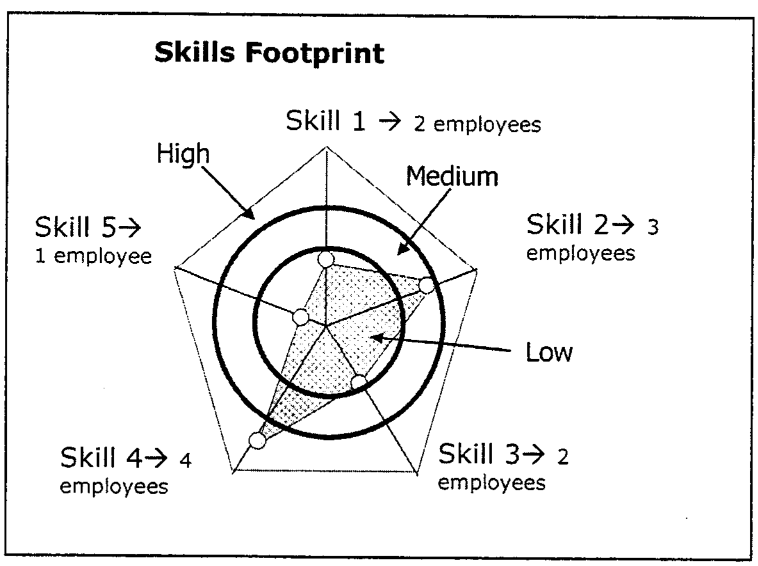


FIGURE 7.31B: SKILLS FOOTPRINT CORRESPONDING TO THE SKILLS MATRIX

As $S_H \rightarrow 1$, the percentage of skills covered by the employees decreases. However, there is an ambiguous interpretation as $S_H \rightarrow 0$, there is a potential combination of either a low or high percentage of skill sets amongst the individual employees, which is resolved by the skill novelty index. Hence, neither index can be used exclusively.

Another concern is that S_H does not distinguish how skills are distributed, as shown in Figures 7.32a and c. In order to be able to distinguish this case, a third measure which complements the other indices must be introduced – the skills cluster index. This is the standard deviation of the percentage of skills i for each employee j:

$$S_C = \frac{1}{N} \bullet \sum_{n=1}^{N} [\sum_{j=1}^{J} \sqrt{\frac{J\sum x_j^2 - (\sum x_j)^2}{J(J-1)}}] \tag{7.35}$$

where x_j is the percentage of available skill sets for each employee j

N is the number of work cells, shifts or departments

J is the number of required employees

Each index conveys important information, but cannot be used individually as there are ambiguities as discussed above. All measures are more informative than the traditional statistical measures: mean and variance. For the three distinct cases shown in Figure 7.32, the mean and standard deviation are identical: 0.20 and 0.408 respectively.

For the 5x5 skills by employee matrix illustrated in Figure 7.32, the three skills indices were calculated for three different cases:

(i) Employee(s) having all the skills (↓).

(ii) The same skill(s) clustered amongst all employees (→).

(iii) The same amounts of skills are distributed amongst all the employees (↘).

For case (i), the amount of employees having all the skills ranges between 1 and 4. For case (ii), all employees have between 1 and 4 skills. For case (iii), each employee has 1 to 4 skills. The skills novelty index, S_N, the skills heterogeneity index S_H and the skills clustering index S_C is calculated for each case. The results are summarized in Table 7.11.

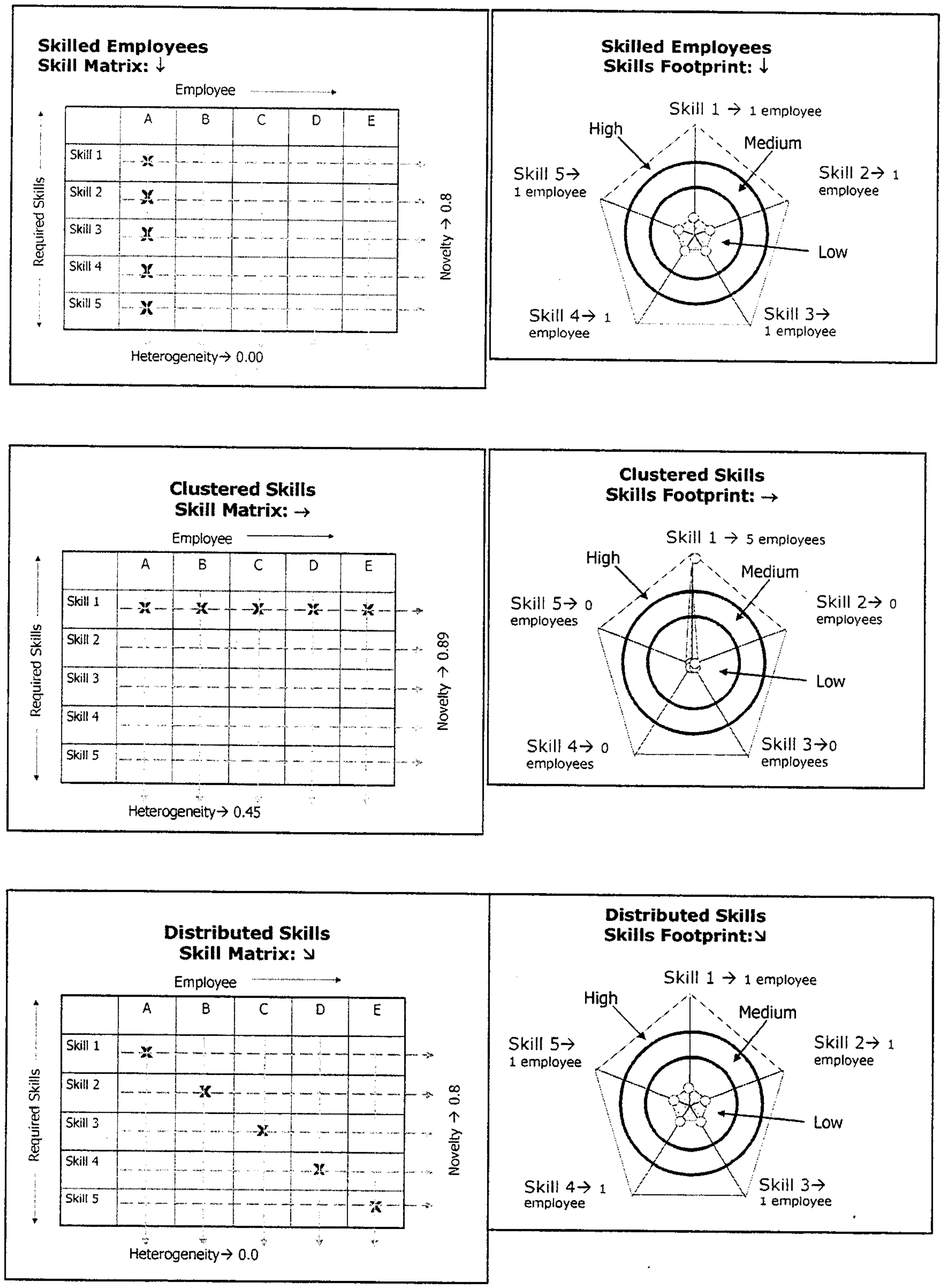


Figure 7.32a,b, and c: Sample Skill Matrices and Their Footprints

Case	Description	# of Skills	S_N	S_H	S_C
(i)	Skilled Employees	1	0.80	0.00	0.45
(ii)	Clustered Skills	1	0.89	0.45	0.00
(iii)	Distributed Skills	1	0.80	0.00	0.00
(i)	Skilled Employees	2	0.60	0.00	0.55
(ii)	Clustered Skills	2	0.77	0.55	0.00
(iii)	Distributed Skills	2	0.60	0.00	0.00
(i)	Skilled Employees	3	0.40	0.00	0.55
(ii)	Clustered Skills	3	0.63	0.55	0.00
(iii)	Distributed Skills	3	0.40	0.00	0.00
(i)	Skilled Employees	4	0.20	0.00	0.45
(ii)	Clustered Skills	4	0.45	0.45	0.00
(iii)	Distributed Skills	4	0.20	0.00	0.00

TABLE 7.11: SKILLS INDICES SUMMARY FOR A 5X5 EMPLOYEES X SKILLS MATRIX

The skills novelty index was plotted from the data in Table 7.11 in Figure 7.33. The novelty is directly related to the distribution of skills in the employee base. This clearly indicates that having skilled employees and skills distributed amongst the employees is better than clustering the skills. This is intuitively correct: whether one employee has all the skills, or the skills are spread among employees, there is complete skill coverage.

The indices based on variance calculations (S_H and S_C) were summed with the skills novelty index and plotted in Figure 7.34. There are three different zones indicating the differences between clustered skill sets, distributing the skill sets among employees and having fully skilled, knowledgeable employees. Clustering the skills or utilizing "islands" of expertise is typical in the dedicated manufacturing systems environment. Whereas distributed skills or completely skilled employees are necessary to be effective in the flexible and reconfigurable manufacturing environment.

Although the mean and standard deviations may be consistent for different scenarios, the skills novelty, heterogeneity and cluster indices are effective it highlighting more relevant information for a participatory manufacturing model.

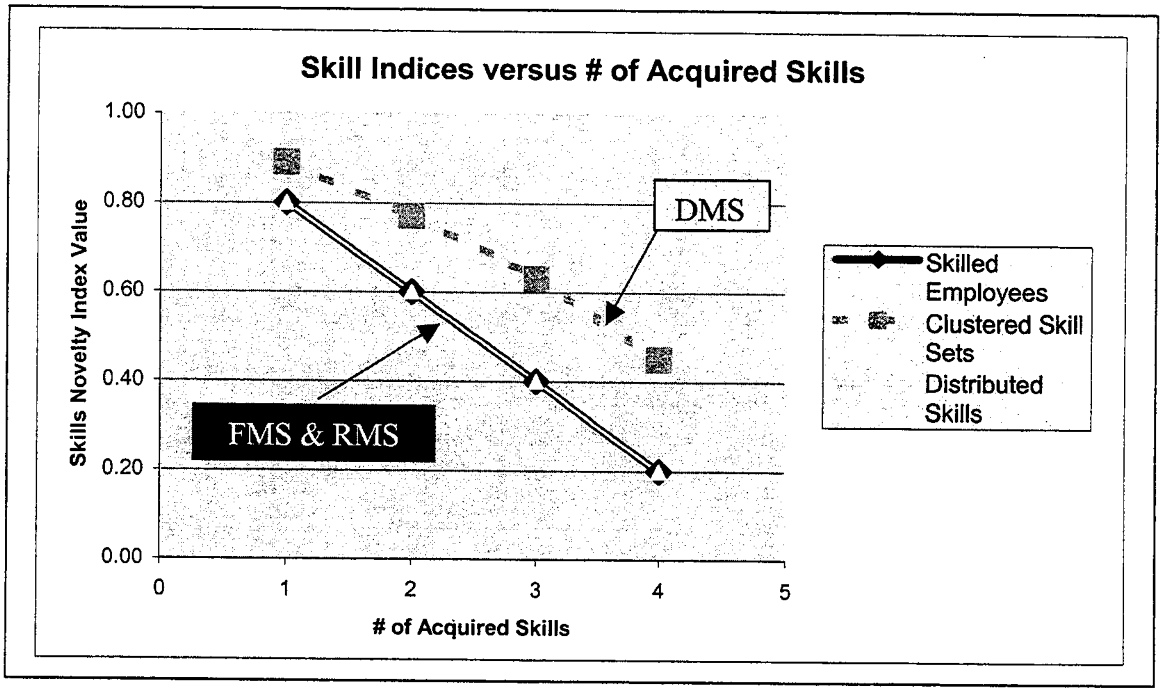


FIGURE 7.33: SKILLS NOVELTY INDEX GRAPH

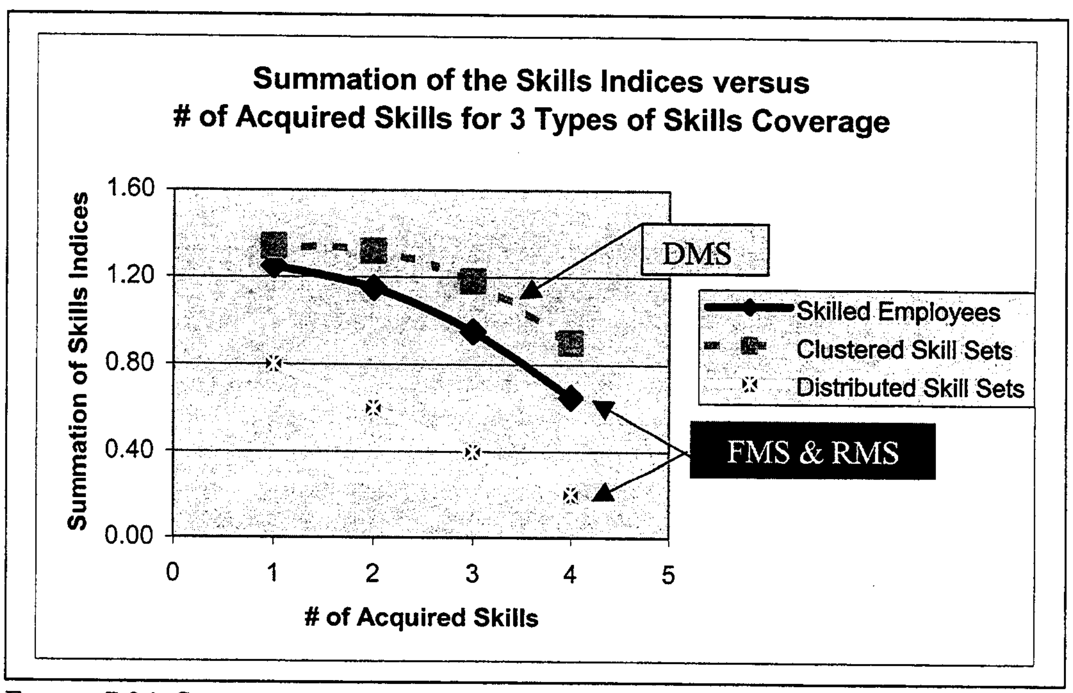


FIGURE 7.34: SUMMATION OF THE SKILLS HETEROGENEITY AND CLUSTER INDICES

7.6 Summary and Conclusions

The initial length of time to perform a task and the number of repetitions required until proficiency is reached is dependent on:

- the diversity of the products and information,
- the complexity of the product, process and operation, or the information content, and
- the personal and professional skill sets of the employees.

A framework was developed to systematically determine diversity, complexity and information content measures at the product, process and operational level. Consequently, complexity indices were introduced, which reflected the interdependent relationships between the different components and levels of complexity. A fundamental constituent of operational complexity is the effort required to perform a task. Effort consists of physical and cognitive elements. The methodology developed in this research considers this.

The matrix analysis methodology can be used to determine a process complexity coefficient, but this is beyond the scope of this research. A comprehensive set of lookup tables or a database system needs to be developed to cover the various manufacturing processes and techniques to effectively determine this measure.

A more comprehensive "cognitive" measure for the quantity of information needs to be developed. People perceive and encode information more effectively if there are graphical aids, standardized terms or other types of memory aides. The information entropy scaling factor only considers the amount of information, not the "quality" or presentation of the information.

Ranking factors were used for physical and cognitive elements when determining effort coefficients. This technique is simple and relatively objective, but it is limited to discrete values, and is only objective within its environment. An alternate method using the Human Model Processor format (e.g. dial caliper versus plug gauges) would provide a relationship based on the task time. Normalizing all tasks based on the longest task time would provide a more objective effort coefficient, as the ranking factors are continuous values that are environment independent.

The skills novelty and heterogeneity indices introduced by Reuer et al [2002+] were modified to reflect a manufacturing environment. To resolve ambiguities, an additional index, the skills cluster index S_C was introduced. Operational complexity is tied directly to the process and product related tasks (at any level), and requires a set of skills, experience or training. The skill level of the employees influences the amount of time (repetitions required) to achieve task proficiency. The skill level measure can be objectively determined by using the skills indices. These indices could be further refined by adding weighting factors.

Utility charts were developed to visualize the effects of the individual parameters on task rate for increasing repetitions (Product Diversity Index, Diversity Ratio, Product and Process Operational Complexity Coefficients, the Effort Coefficient, Information Entropy and Number of Repetitions). The output was plotted for the three different skill levels.

The various measures and relationships must now be tied into a human performance model. The learning curve phenomenon is used as the base model: the above parameters must be linked to the learning curve parameters. This is developed in the next chapter.

8.0 LEARNING CURVE PARAMETERS

As stated in the introduction, the goal is to define a mathematical model which combines human performance parameters with standard performance parameters such as machine utilization, defects, and work in process. This is extremely challenging, as there are no solid predictive models for human characteristics (such as behaviour) or cognitive processes, although much interesting work has been initiated. However with the trends in technology and business strategies today, this is a relevant topic for research and is best suited being conducted using Systems Analysis and Design techniques.

The learning curve is an observable phenomenon which directly correlates human performance to system performance; hence, the real and costly necessity for "ramp up time" or a "launch curves" for any new product or process. The variables that influence the learning curve (such as diversity and complexity) are not well understood and vary from environment to environment; hence, the focus in defining a framework to objectively evaluate them. Now, to create a participatory manufacturing model, the learning curve model must be linked to variables such as complexity and skill sets. Understanding the human performance variables within a manufacturing system can highlight system sensitivities at the design stage.

A series of assumptions need to be made.

(1) Assume the general model is deterministic.

(2) Assume that the number of repetitions to achieve proficiency is related to the:

- (i) operational complexity index
- (ii) employee skill levels and skills mix
- (iii) task time and the number of subtasks
- (iv) attitude and behaviour
- (v) corporate culture

(3) The time to perform the first task varies based on the operational complexity index, employee skill levels and skills mix.

(4) Assume product diversity is not an influence for this model.

(5) Assume good memory, cognitive processing and problem solving abilities are inclusive, or in other words, someone with good memory skills also has the other cognitive skills.

(6) Using the working memory phenomenon as a baseline, assume that the information content can be "processed" by 7±2 "chunks". "Low" memory processing skills corresponds to 5 chunks, and medium and high to 7 and 9 chunks respectively.

(7) This is a provisional model: the validity of the model needs to be confirmed with experimental data.

From chapter 7, the learning curve is:

$$p_t(i) = p_t(1) \quad * i^n \tag{7.1}$$

where $p_t(i)$ and is the time to produce the i^{th} unit or generate the i^{th} task.

$p_t\,(1)$ is the time to produce the first unit or generate the first task.

i is the cumulative unit or task repetition number.

n is the learning index.

$$p_t(1) \propto f(OI, skill\ sets) \tag{8.1}$$

$$n \propto f(OI, skill\ sets, task\ time, attitude, corporate\ culture) \tag{8.2}$$

8.1 Memory

Memory processes consist of encoding, maintenance and retrieval. Encoding involves packaging or organizing information into "chunks" and rules for interpretation and retrieval. Although the mechanisms for converting information from working memory or long term memory are not well understood, some analogies can be made. The memory content is proportional to the information content, and an individual's "chunking ability". The quantity of information N is represented by the information entropy H, or the logarithm to the base 2 of N. Processing "chunks" is the equivalent of dividing the information by chunks or:

$$\boxed{\textit{Cognitive Factor} = \frac{\textit{Information Quantity}}{\textit{Chunking Ability}}}$$

As this is an exponential function, mathematically this is represented by:

$$Factor_{cognitive} = H - \log_2 Chunking_{level} \tag{8.3}$$

where $Factor_{cognitive}$ is the memory or cognitive processing factor,

H is the information entropy, and

$Chunking_{level}$ is the representative value of the chunking ability level.

Table 8.1 lists the chunking ability levels.

However, this is only true if all skill sets and experience are available. If this is not true, (i.e. $S_N \neq 0$), the employees must accumulate additional information, experience, knowledge, and application rules. It is assumed that the amount of information to be accumulated is related to both the cognitive and the skills novelty index, in the form of:

$$Factor_{cognitive} = H - \log_2 Chunking + a_0 * S_N \tag{8.4}$$

where a_0 is a weighting factor dependent on the physical and cognitive effort to learn the necessary skills, and the number of employees who require the necessary skills (Figure 8.1).

Level	**Value**	**Log**	**Factor**
Low	5	$\log_2 5$	2.32
Medium	7	$\log_2 7$	2.81
High	9	$\log_2 9$	3.17

TABLE 8.1: CHUNKING FACTORS

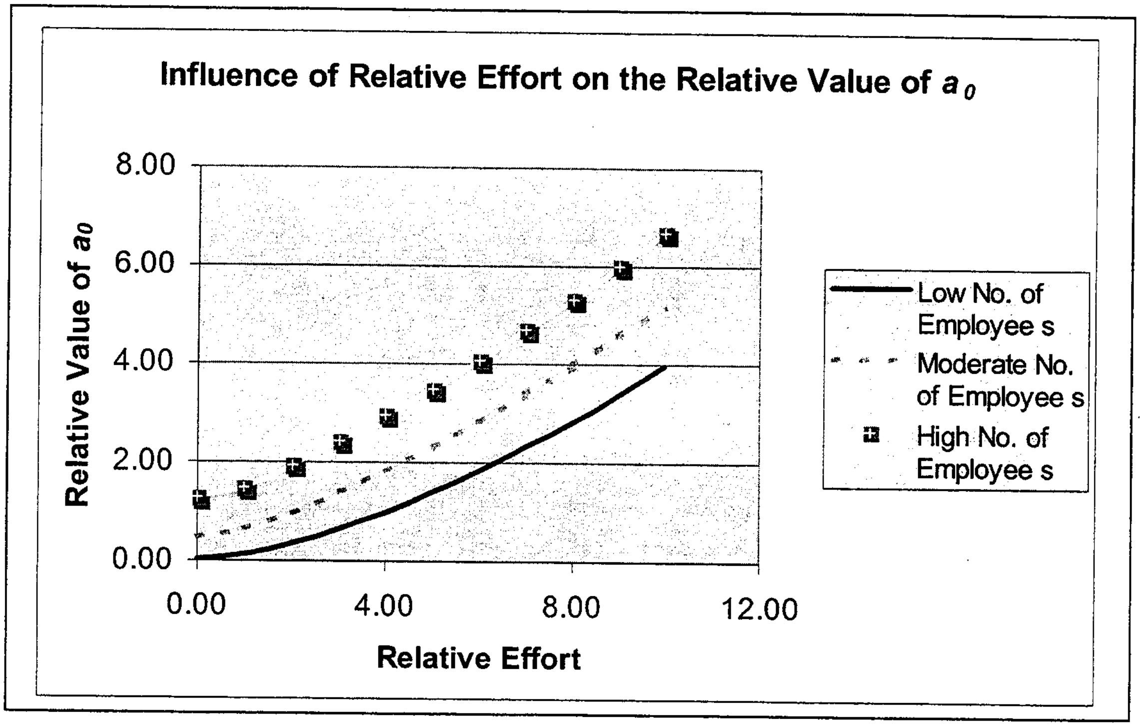


FIGURE 8.1: INFLUENCE OF EFFORT ON THE RELATIVE VALUE ON a_0

Fatigue reduces the ability to acquire skills and knowledge, but fatigue is not a "continuous" phenomenon. Its effects will manifest themselves during an irregularly scheduled midnight shift, or accumulated overtime, and weekend work. For the sake of this model, fatigue will be considered when the analysing weighting factors with respect to the learning curve in section 8.2.

Let us rewrite equations 8.1 and 8.2 as:

$$p_t(1) \propto K_{factor}[(D_{R_{product}} + c_{o,product}) * Factor_{cognitive_{product}} + (D_{R_{process}} + c_{o,process}) * Factor_{cognitive_{process}}] \quad (8.5)$$

where K_{factor} is a weighting factor dependent on the skills heterogeneity and clustering indices;

$D_{Rproduct}$ and $D_{Rprocess}$ are the diversity ratios for the product and process constituents for the operational complexity index; and

$c_{o,product}$ and $c_{o,process}$ are the relative complexity coefficients for the product and process constituents for the operational complexity index.

$$n \propto \frac{-1}{X_{factor}[(D_{R_{product}} + c_{o,product}) * Factor_{cognitive_{product}} + (D_{R_{process}} + c_{o,process}) * Factor_{cognitive_{process}}]} \tag{8.6}$$

$$X_{factor} = f(a_1, a_2, a_3, a_4, ...a_m) \tag{8.7}$$

where X_{factor} is the weighting factor suitable to a particular environment. For this research $m = 5$. The coefficients are listed as follows:

a_1 is a function of the skills heterogeneity and cluster indices,

a_2 is a function of the number of tasks or motions, task time and interruptions,

a_3 is a function of attitude and behaviour,

a_4 is a function of the corporate culture "dynamics", and

a_5 is a function of the corporate culture environment.

The format of the X_{factor} function is context sensitive: in certain situations one coefficient could have a scaling or multiplicative influence on another coefficient. In another situation, the same coefficient may have no influence and should not be included in the model. Rules or heuristics need to be applied to determine the type and quantity weighting coefficients, and the format of the scaling function.

However, independent of the final format of the X_{factor} function, the relationship between increases in complexity, quantity and diversity of information, and other negative influences (reflected by higher values of the various coefficients as described by equation 8.7) must result in a longer learning period in order to achieve proficiency. This is achieved by the expression for the learning index n in equation 8.6.

The coefficients cannot be determined through direct mathematical analysis; however as with the model of the scaling function, rules or heuristics can be applied to gain insight into some general values, which can be used in the final learning curve model. Presented here are heuristics that satisfy the "test of reasonableness", and relative values of the coefficients that captures the importance of different scenarios. To be robust, the coefficients and the weighting factor model need to be coupled with experimental data, rules, and probability curves derived from the different manufacturing settings described in chapters two, three and four.

8.2 Coefficient Determination

8.2.1 Skills Coefficient: a_1

The skills coefficient a_1 is a function of the skills indices, the quantity of skills and employees, and the functional requirements of the job: it is ideal having all employees be proficient in all skills; however, in reality this may not be feasible due to the requirements based on the division of labour, employee movement, scheduling and training. In order to determine a relative value for the skills coefficient a_1, the **basic** needed skill requirements must be compared to the available skills. An abundance of skills adds "no value", but a dearth of skills leads production and training issues, increasing the value of a_1. Figure 8.2 illustrates the utility curves to describe this phenomenon – note that the plateau levels are situation dependent. The requirements comparison must be tied into the skills indices developed in chapter seven.

Optimal scheduling of resources for production and training is beyond the scope of this work – the goal is to generate reasonable heuristics for the value of the skills coefficient a_1.

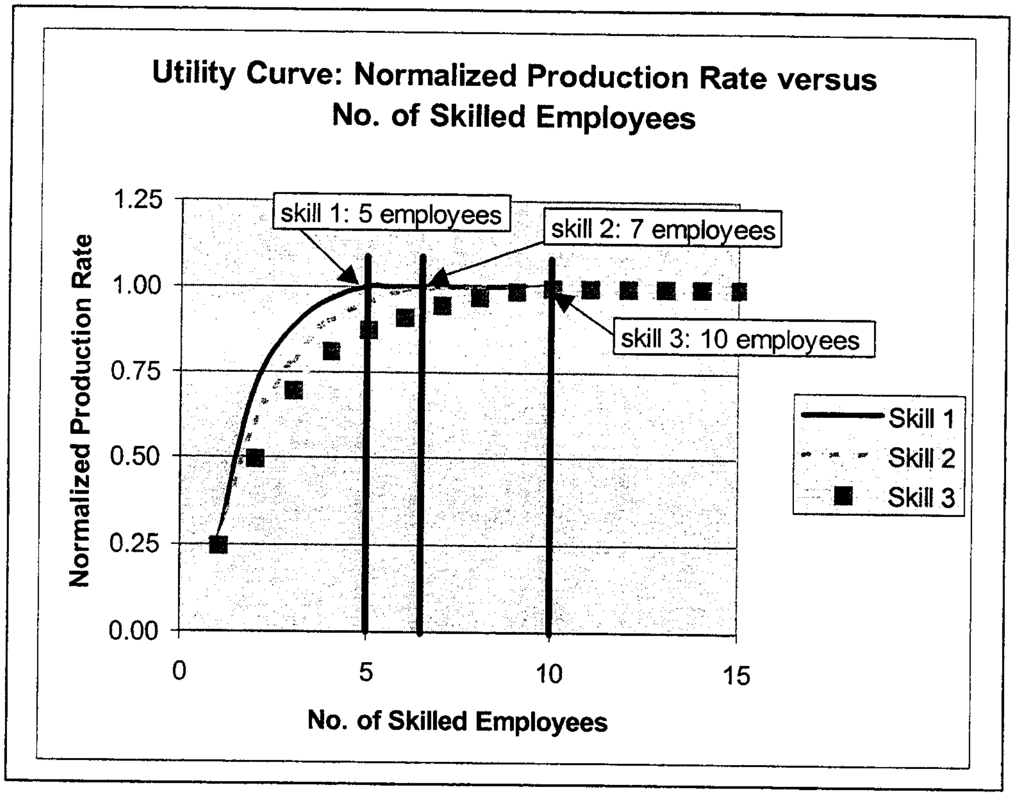


FIGURE 8.2: UTILITY CURVE: AVAILABLE SKILLS VERSUS PRODUCTIVITY

First, the functional requirements for the amount of skills must be determined. This is illustrated by the following example: assume we have a 5 x 5 skill versus employee matrix, with the requirements listed in Figure 8.3a, and the skills footprint is shown in Figure 8.3b.

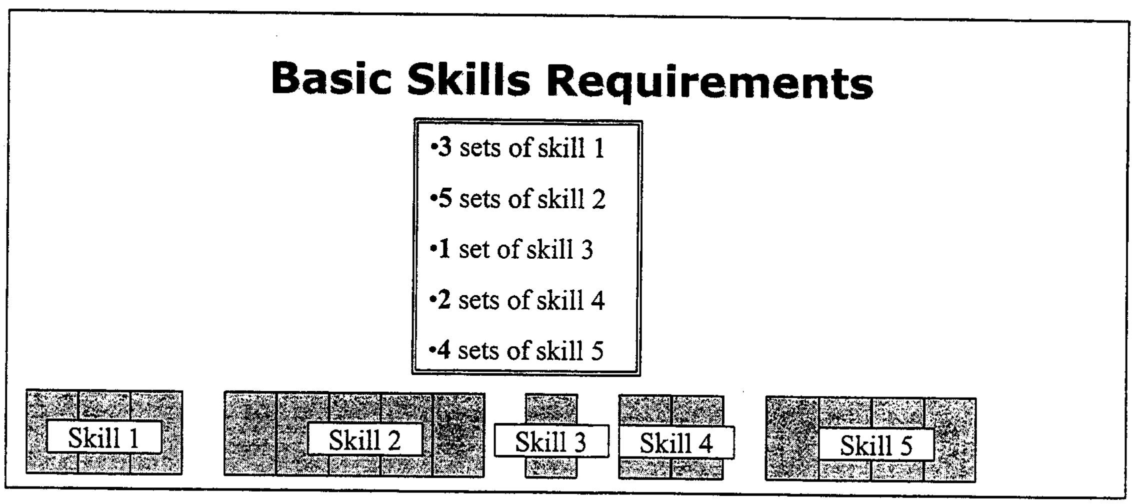


FIGURE 8.3A: BASIC SKILLS REQUIREMENTS

There are many subsets of the skills-employee matrix that satisfy the requirements, but insight as to the effect of not meeting the basic skills requirements is investigated here.

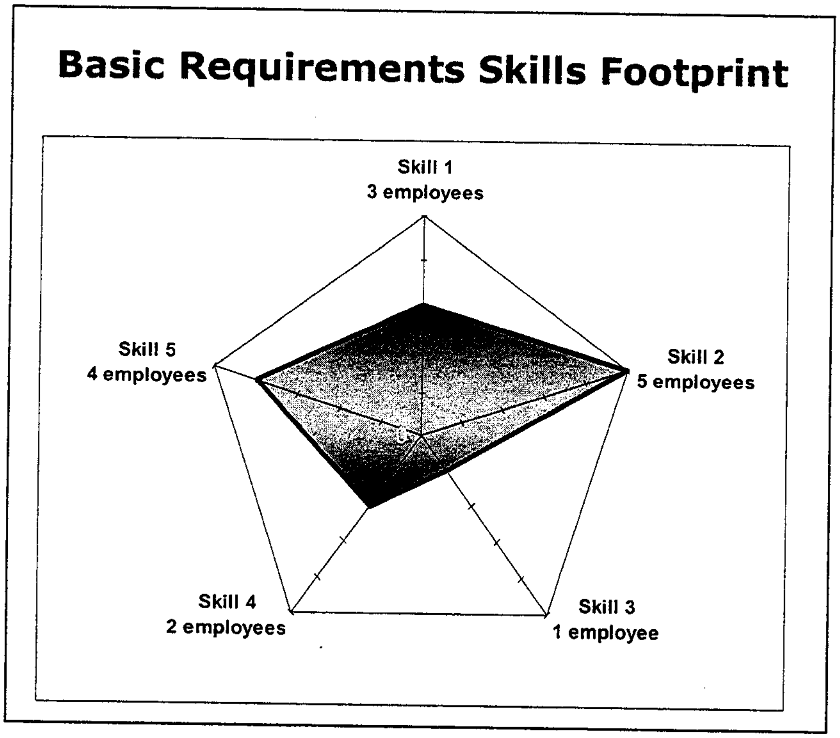


FIGURE 8.3B: BASIC SKILLS REQUIREMENTS FOOTPRINT

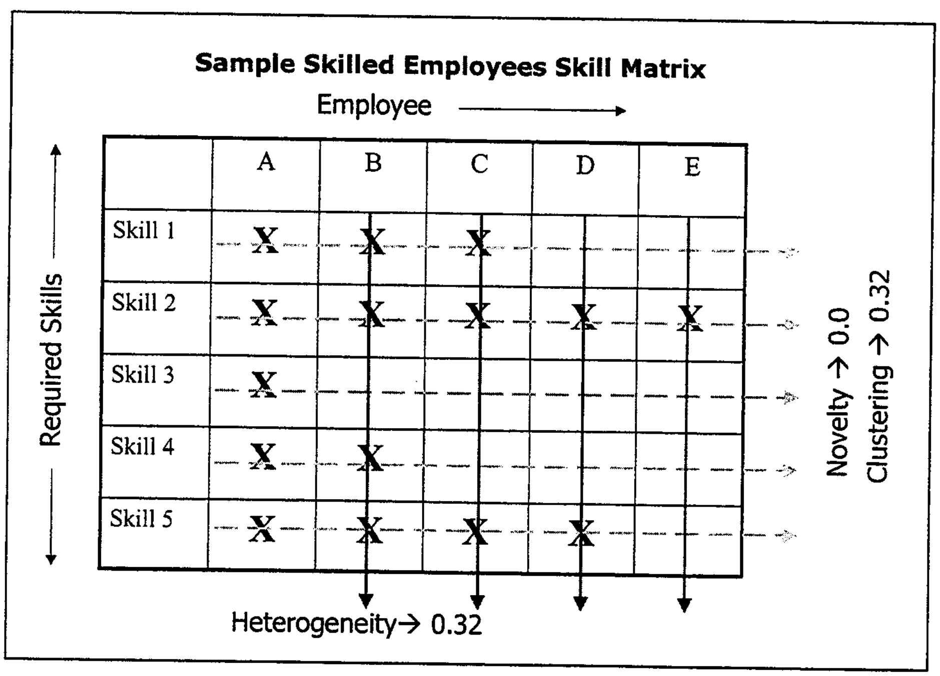


FIGURE 8.3C: SAMPLE SKILLS VERSUS EMPLOYEE MATRIX THAT SATISFIES THE REQUIREMENTS

For a the 5 x 5 skills versus employee matrix that meets the requirements (shown in Figure 8.3c) the skills novelty index, S_N the skills heterogeneity index, S_H and the skills clustering index, S_C respectively are: 0.0, 0.32 and 0.32. For this case, the value of the skills coefficient a_I would be low, but not zero. This reflects the fact that scheduling conflicts could occur as only the minimum basic requirements are being met; hence, this coefficient will have a minor influence on the overall time to achieve proficiency. As the skills heterogeneity index, S_H and the skills clustering index, S_C approach zero, surplus talent is available (shown in Figure 8.4); therefore, the value of a_I becomes zero.

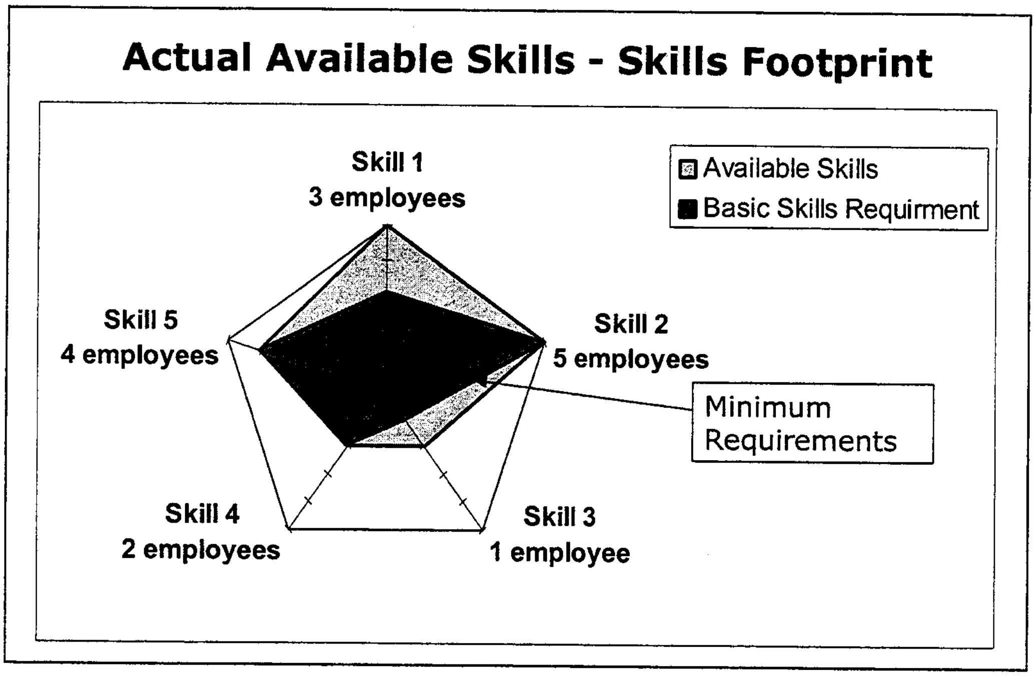


FIGURE 8.4: SKILLS FOOTPRINT SHOWING SURPLUS TALENT

But what if the basic requirements are not met? The criteria is broken down into these general groups:

- incomplete skills coverage, but partial coverage of all skills, i.e. $0 > S_N \geq 0.30$
- no coverage for a low percentage of skills, i.e. $0.31 > S_N \geq 0.60$
- no coverage for approximately half the required skills, i.e. $0.61 > S_N \geq 0.90$
- no coverage for most of the required skills, , i.e. $S_N \geq 0.91$

Table 8.2 summarizes the effects of the four scenarios on the skills coefficient a_I in combination with the skills novelty index, and the distribution of skills amongst the employees. The skill distribution is represented as the summation of the skills heterogeneity and clustering indices (based on the available skills). The summation of the actual values of the skills heterogeneity and clustering indices is compared to the summation of the skills heterogeneity and clustering indices for the "basic level". The results for value of the skills coefficient a_I correspond to different relative values, as shown in Table 8.2 and Figure 8.5. The actual values are dependent on the quantity of skills to be acquired, the amount of employees and the effort to learn the skills.

Skill Novelty Index, S_N	**Skill Heterogeneity Index + Skill Clustering Index $S_H + S_C$**	**Relative Value of a_I**	**Comment**
0	Actual $S_H + S_C <$ ½ Basic $S_H + S_C$	0	Surplus talent, no scheduling issues
0	Actual $S_H + S_C \geq$ ½ Basic $S_H + S_C$	0.5	Meets the basic requirements, and surplus talent may be available, but scheduling conflicts may occur.
0.01 – 0.30	Actual $S_H + S_C <$ Basic $S_H + S_C$	1	Incomplete skills coverage, **consistent** mix of employee skills
0.01 – 0.30	Actual $S_H + S_C \geq$ Basic $S_H + S_C$	2	Incomplete skills coverage, **inconsistent** mix of employee skills
0.31 – 0.60	Actual $S_H + S_C <$ Basic $S_H + S_C$	2	**No coverage** of a **low percentage** of skills, but redundancy in other areas
0.31 – 0.60	Actual $S_H + S_C \geq$ Basic $S_H + S_C$	3	**No coverage** of a **low percentage** of skills, difficulty scheduling in some other areas
0.61 – 0.90	Actual $S_H + S_C <$ Basic $S_H + S_C$	3	**No coverage** of a **moderate percentage** of skills, but potential redundancy in other areas.
0.61 – 0.90	Actual $S_H + S_C \geq$ Basic $S_H + S_C$	4	**No coverage** of a **moderate percentage** of skills, difficulty scheduling in most other areas
> 0.91	N/A	5	No coverage – extensive training is required. This significantly affects both the time to be proficient and the quality of the output.

TABLE 8.2: INFLUENCES ON THE VALUE OF THE SKILLS COEFFICIENT a_I

Figure 8.6a and 8.6b each illustrate a skills footprint that corresponds to the case where $0 > S_N \geq 0.30$, where there is a consistent mix of employee skills (Figure 8.6a), and a divergent set of employee skills (Figure 8.6b). The other cases have a similar footprint only the area is reduced as the amount of available skills is reduced (the skills novelty index increases).

A lookup table or expert system is required to "fine tune" the value of a_1. A weighting factor based on the amount of employees and skills is necessary. For example, different results would occur for a 10 x 10 skills-employee matrix as compared to a 5 x 5 skills-employee matrix with the equivalent values for the skills indices. The larger the skills-employee matrix, the longer it takes to achieve proficiency.

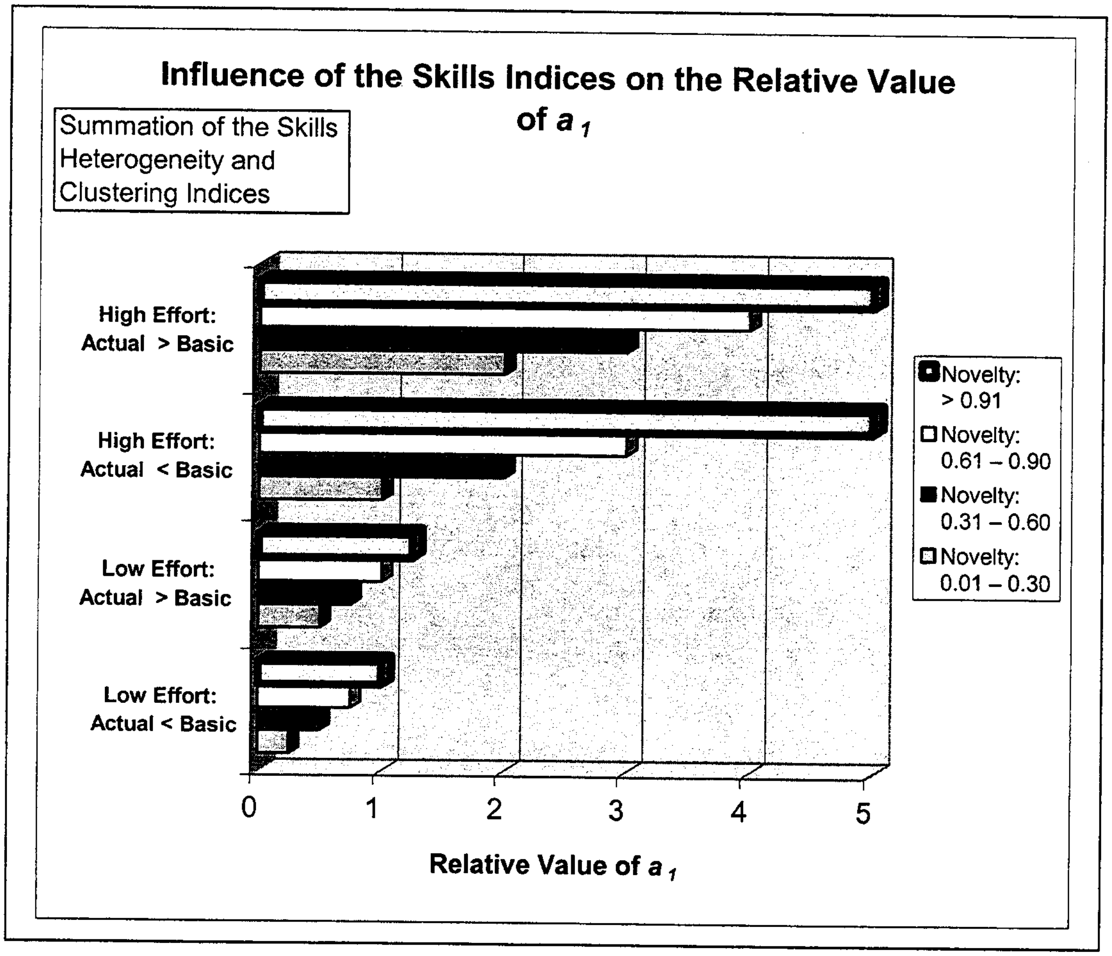


FIGURE 8.5: INFLUENCE OF THE SKILLS INDICES ON THE RELATIVE VALUE OF a_1

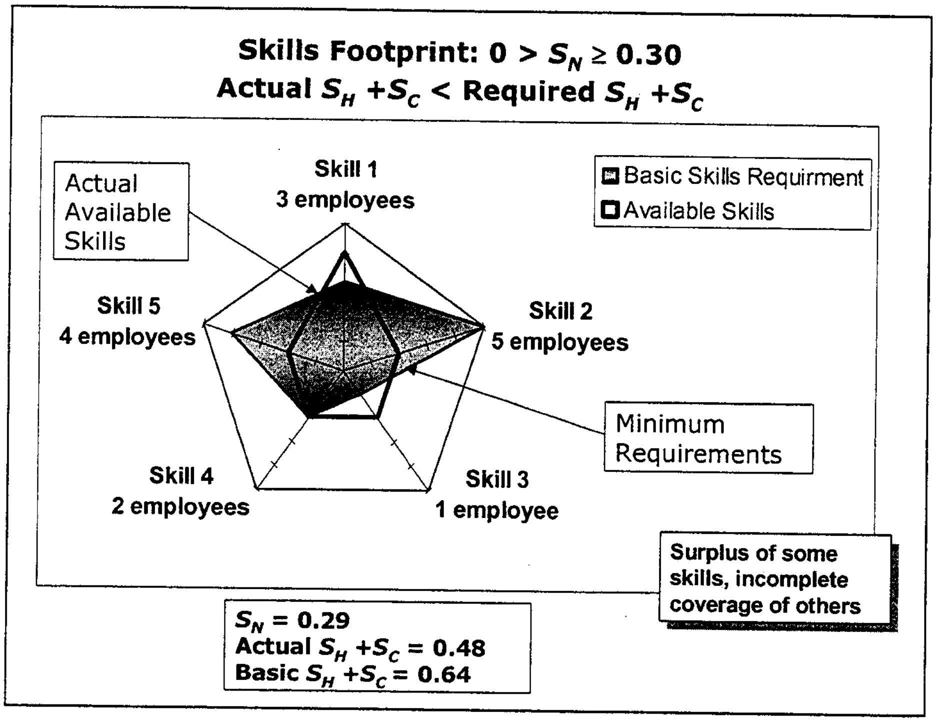


FIGURE 8.6A: FOOTPRINT FOR A LOW SKILLS NOVELTY INDEX WITH CONSISTENT SKILL LEVELS

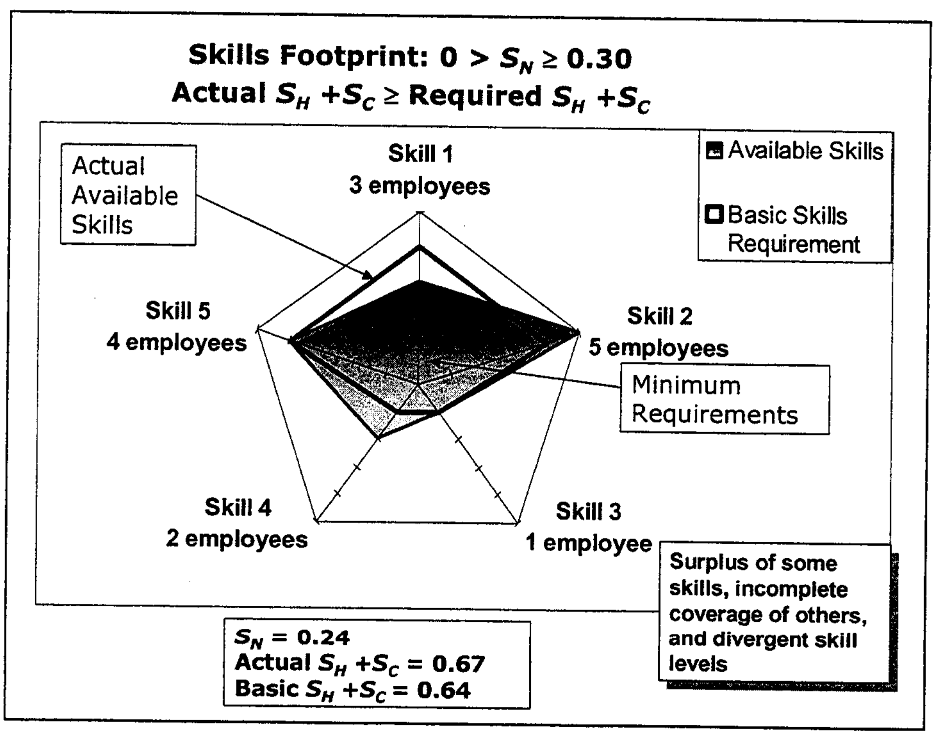


FIGURE 8.6B: FOOTPRINT FOR A LOW SKILLS NOVELTY INDEX WITH DIVERGENT SKILL LEVELS

8.2.2 Task Coefficient: a_2

The task coefficient a_2 is a function of the task time, cycle time, task quantity, and the number of cycles. Tasks are considered to be direct or indirect in this application. Direct tasks are steps or work required in the manufacturing process. Indirect tasks consist of ancillary functions such as gauging, data collection, monitoring, changing tools, and so forth. There are two general task factors to be considered, as shown below:

$$Task\ Factor_1 = \frac{Task\ Time}{Cycle\ Time} \tag{8.8}$$

$$Task\ Factor_2 = \frac{Task\ Quantity}{No.\ of\ Cycles} \tag{8.9}$$

For direct tasks, the task time is equal to or less than the cycle time, but this is not true for indirect tasks. For example, for high volume production of a cylinder block, the cycle time is in the order of seconds, but gauging a part is in the order of minutes. A comparison of the various production environments using these parameters is shown in Figure 8.7. Figure 8.8 illustrates the difference between a direct task and an indirect task.

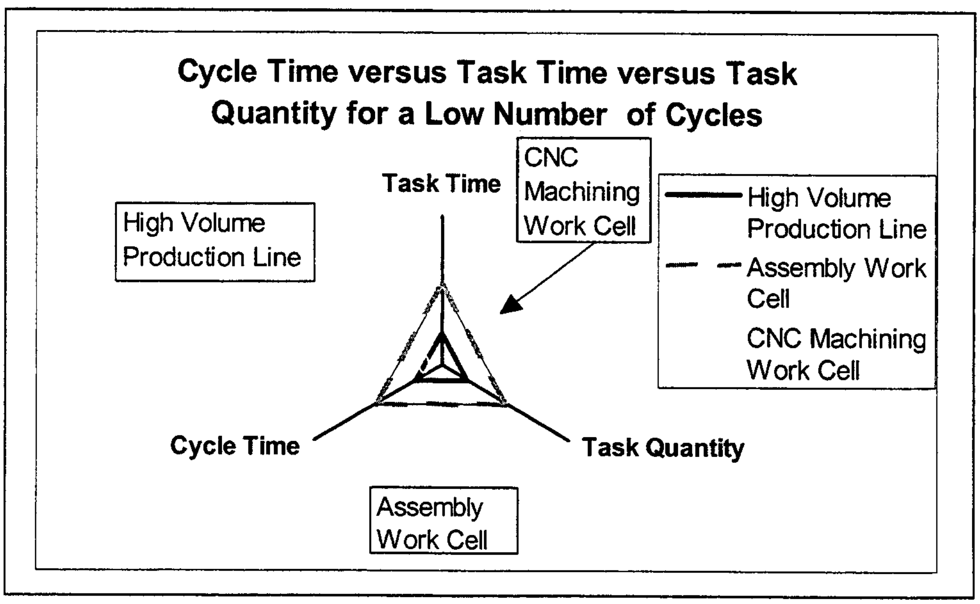


FIGURE 8.7: COMPARISON OF TASK PARAMETERS TO DIFFERENT PRODUCTION ENVIRONMENTS

The task quantity to cycle ratio (or task frequency) differs between direct to indirect tasks. Data collecting, tooling changes or gauging may occur every x parts, whereas y bolts may be tightened to a specific torque every cycle. Both these task factors as well as the individual components influence the value of a_2. Table 8.3 provides a general summary of the different scenarios, embracing high volume production to low volume work cell tasks. Grayed out areas are non-common scenarios.

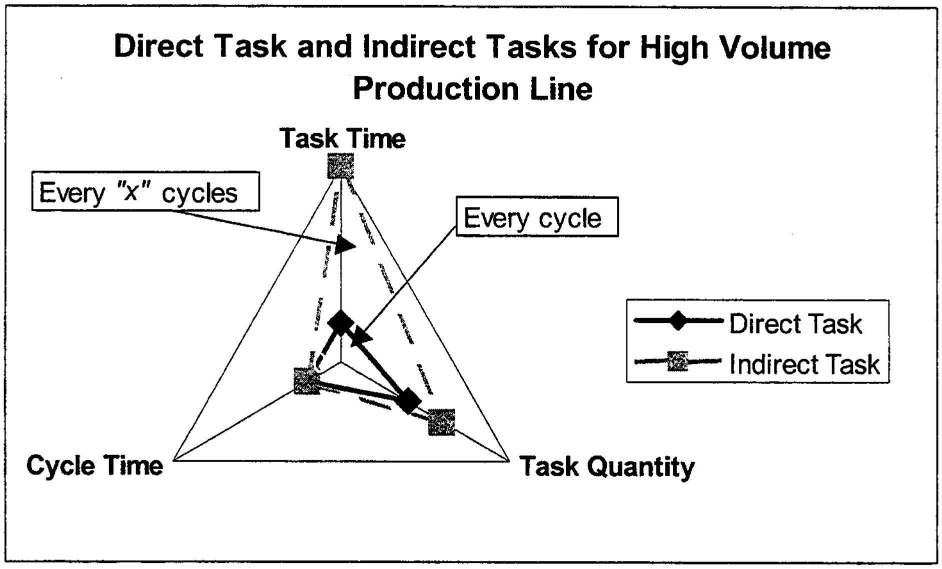


FIGURE 8.8: DIRECT TASKS AND INDIRECT TASKS

Although interesting to contemplate, there is no direct relationship between the area of the triangle in Figures 8.7 and 8.8 and the value of the task coefficient a_2. Consider the following example illustrated in Table 8.4 and Figure 8.9: the values for the axes generate the same 3-D surface area - 2.6 "task-time" units.

	Task Time (minutes)	Task Quantity	Cycle Time (minutes)
Assembly Task	0.8	4	1
Work Cell	4	1	0.8

TABLE 8.3: TASK COEFFICIENT EXAMPLE

Cycle Time	Task Time	Task Quantity	# of Cycles	Comment
Low	Low	Low	Low	Direct Task: High Production Assembly Line
Low	High	Low	Low	Indirect task: batch test
High	Low	Low	Low	Direct Task: Work Cell
High	High	Low	Low	Direct or Indirect Task: Work Cell → pressure testing engine components for leakage
Low	Low	High	Low	Direct Task: Assembly Line with common sub-tasks such as tightening multiple bolts to a specific torque level.
Low	High	High	Low	Indirect task – inspection of a part per batch
High	Low	High	Low	Direct Task: loading / unloading a pallet
High	High	High	Low	Direct or Indirect Task: Work Cell
Low	Low	Low	High	Indirect Task: checking a criterion → 1 out of every 100 parts (dedicated production line)
Low	High	Low	High	Indirect Task: extensive gauging or testing → 1 out of every 100 parts (dedicated production line)
High	Low	Low	High	Indirect task: changing tools in a CNC machine
High	High	Low	High	
Low	Low	High	High	Indirect task: block tool change of "quick change" tools
Low	High	High	High	Indirect task: extensive block tool change of difficult to manipulate (heavy, large) tools → broach
High	Low	High	High	
High	High	High	High	Indirect Task: extensive gauging or testing → 1 out of every 100 parts (work cell)

TABLE 8.4: TASK COEFFICIENT PARAMETERS

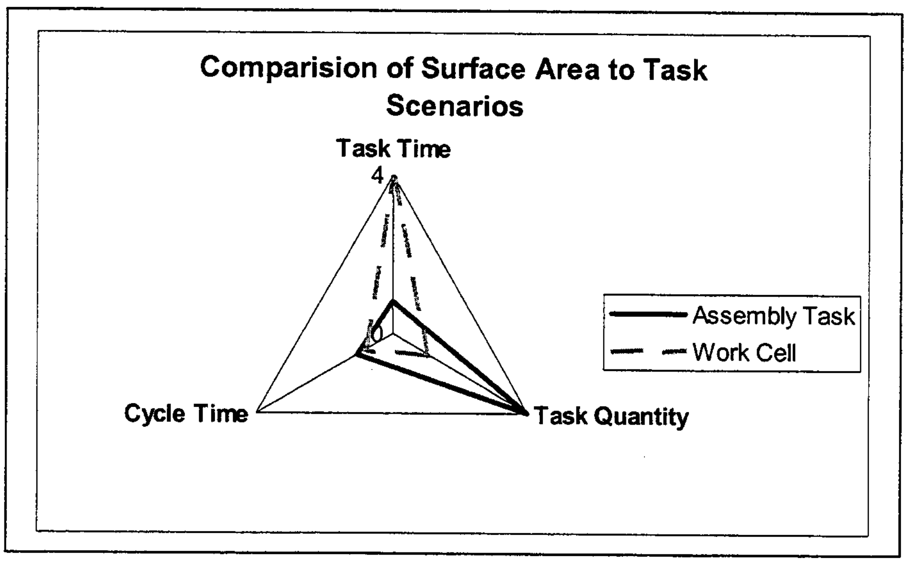


FIGURE 8.9: COMPARISON OF SURFACE AREA TO TASK COEFFICIENT VALUE

The amount of repetitions needed to achieve proficiency is significantly different for these two scenarios: performing four tasks quickly indicates that the tasks are physically and cognitively effortless, while the opposite is true if a task requires several minutes. Hence the need for another perspective other than the absolute values of task time, cycle time and task quantities. These parameters must analyzed in conjunction with the task factors identified in equations 8.8 and 8.9. The values of the task factors are summarized below in Table 8.5:

	Task Factor$_1$	Task Factor$_2$	a_2
Assembly Task	0.8	4	Low
Work Cell	5	1	Medium

TABLE 8.5: TASK FACTOR VALUES FOR EXAMPLE

Hence the value of a_2 is situation dependent. However, several inferences can be made on these parameters.

As the Task Factor$_1$ ratio $\rightarrow\infty$, the probability of interruptions increases. The time duration and quantity of interruptions affects the learning curve, i.e. the amount of repetitions to get to a proficient level increases. This becomes more prevalent if the task frequency is low. Hence as the Task Factor$_1$ ratio $\rightarrow\infty$, the value of a_2 increases, as shown in Figure 8.10.

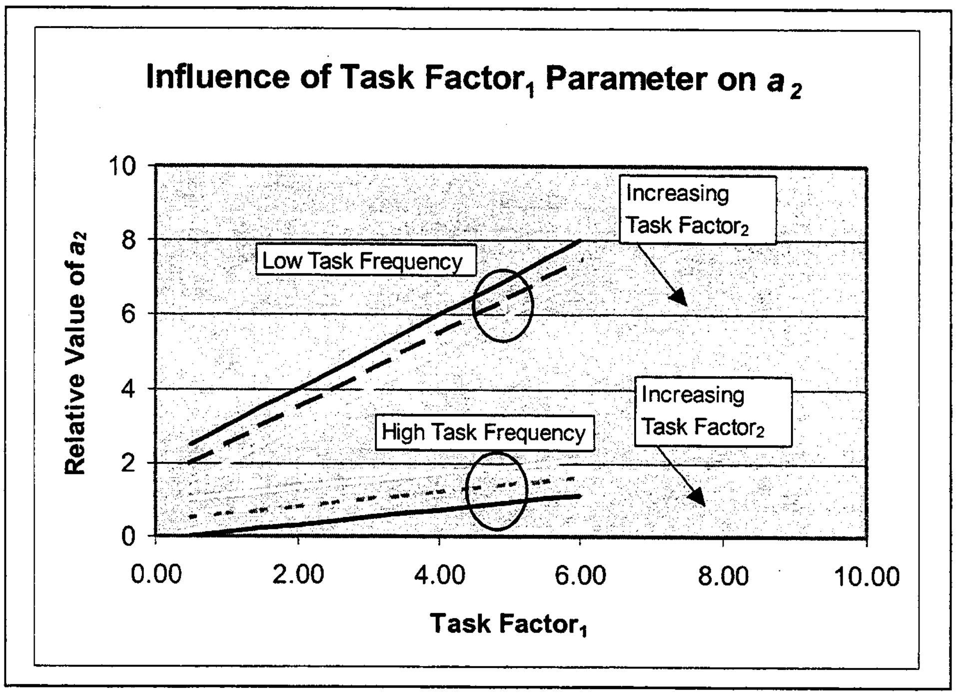


FIGURE 8.10: INFLUENCE OF TASK FACTOR$_1$ ON THE RELATIVE VALUE OF a_2

For a high volume production line, the opposite affect occurs as the Task Factor$_2$ ratio $\rightarrow\infty$. This indicates that there are several common subtasks that must be performed during a cycle. Proficiency will occur quickly; hence the value of is a_2 small (Figure 8.11).

As can be seen by Figures 8.10 and 8.12 the task factors have inverse effects on the value of the task coefficient a_2; consequently, some rules or heuristics are needed with to consider the influences of the various factors to determine a value of a_2. Some sample rules to generate values of a_2 follow in Table 8.6. As with the skills coefficient a_1, a lookup table or expert system is required to "fine tune" the value of a_2.

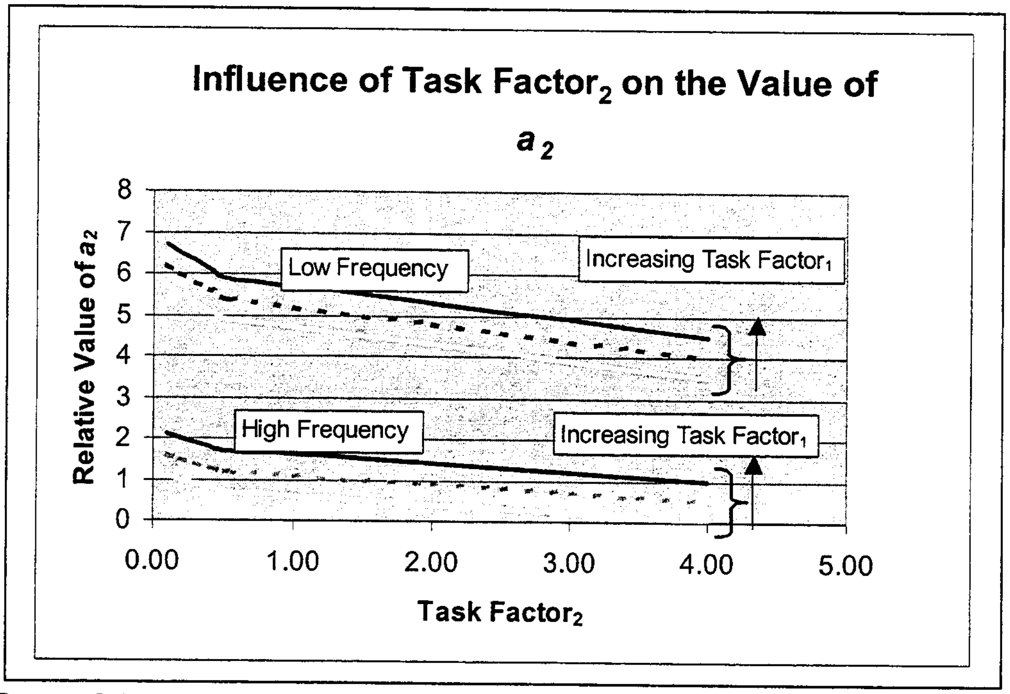


FIGURE 8.11: INFLUENCE OF TASK FACTOR$_2$ ON THE RELATIVE VALUE OF a_2

8.2.3 Attitude and Behaviour Coefficient: a_3

Attitude and behaviour are variable elements that influence human performance. Recall from chapter 5 that the mechanisms that govern attitude and behaviour are not well understood. Any models that exist are descriptive in nature; however, the effect of attitude on performance can be analysed statistically, as illustrated in Figure 8.12. Here a probability distribution is plotted with respect to operator availability. Most employees wish to perform and are available a high percentage of the time, but even the "best" cannot be 100% available.

IF	AND	THEN
Cycle time is short	Direct task time < cycle time	$a_2 \rightarrow$Low
Direct task time << Cycle time	No indirect tasks	$a_2 \rightarrow$Low Boredom Factor
Indirect task time >> Cycle time	Task quantity << no. of cycles	$a_2 \rightarrow$High
Task Factor$_1$ $\rightarrow$1 for direct tasks	Indirect tasks exist	High probability of interruptions $\rightarrow$ High
Task Factor$_2$ >>1	For direct tasks	$a_2 \rightarrow$Low Learn task(s) quickly
Cycle time is long	Task Factor$_2$ >>1	$a_2 \rightarrow$Low Boredom Factor

TABLE 8.6: SAMPLE TASK COEFFICIENT RULES

The probability of poor performers drops off exponentially - at the extreme end is 0% availability, which constitutes absenteeism (a very real problem is the workplace). The constants defining this curve (level of skewness, kurtosis) will vary between different environments, but the trend analysis is consistent for all environments. Obviously, the percentage availability has a direct influence on the amount of repetitions to become proficient as constant interruptions of the learning process occur.

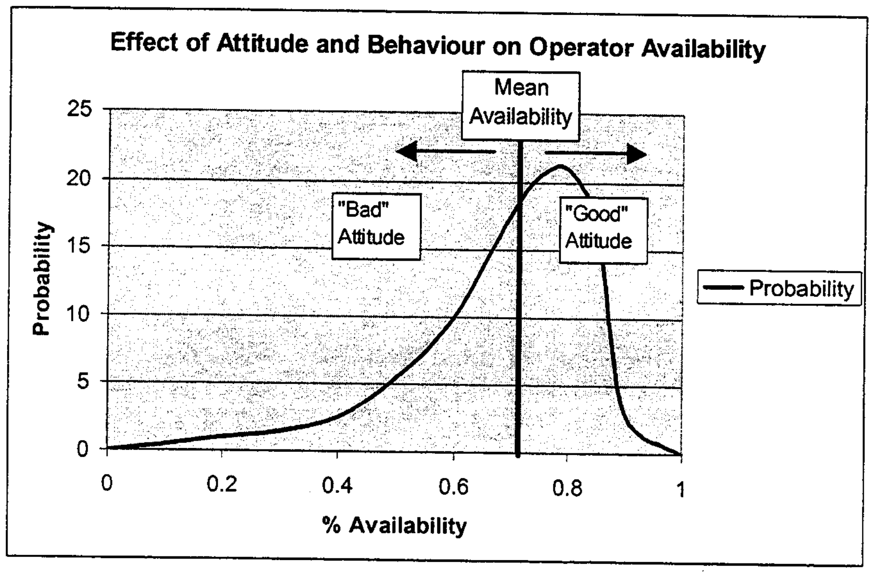


FIGURE 8.12: TREND ANALYSIS ILLUSTRATING THE EFFECT OF ATTITUDE AND BEHAVIOUR ON OPERATOR AVAILABILITY

The inverse of this curve can be used to describe the time to perform a given task as illustrated in Figure 8.13. This is not directly used in the learning curve performance model; however, if a discrete simulation incorporated a "human performance variation" equivalent to normal process variations, the model would yield results based on the sensitivity to human participation.

This analysis can be extended to incorporate cooperation and conflict as well. Mathematically, cooperation can be said to consist of greater than 100% operator availability as more than one person is involved when performing a task. Figure 8.14 shows this phenomenon. A mean shift occurs and there is no chance of complete absenteeism. The converse can be said to occur in a conflict environment. If two or more persons cannot function together, the mean availability is reduced (in reality, this can be significant).

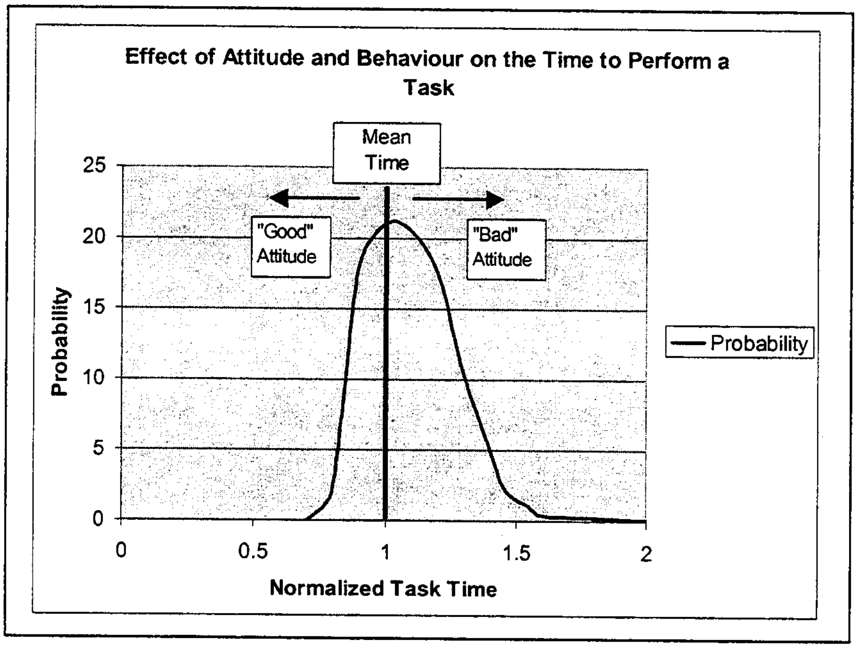


FIGURE 8.13: TREND ANALYSIS ILLUSTRATING THE EFFECT OF ATTITUDE AND BEHAVIOUR ON TASK TIME

In order to generate deterministic rules, the percent availability graph was divided into five zones:

- 0 – 40% availability
- 40-60% availability

- 60-75% availability
- 75-82% availability
- 82-100% availability

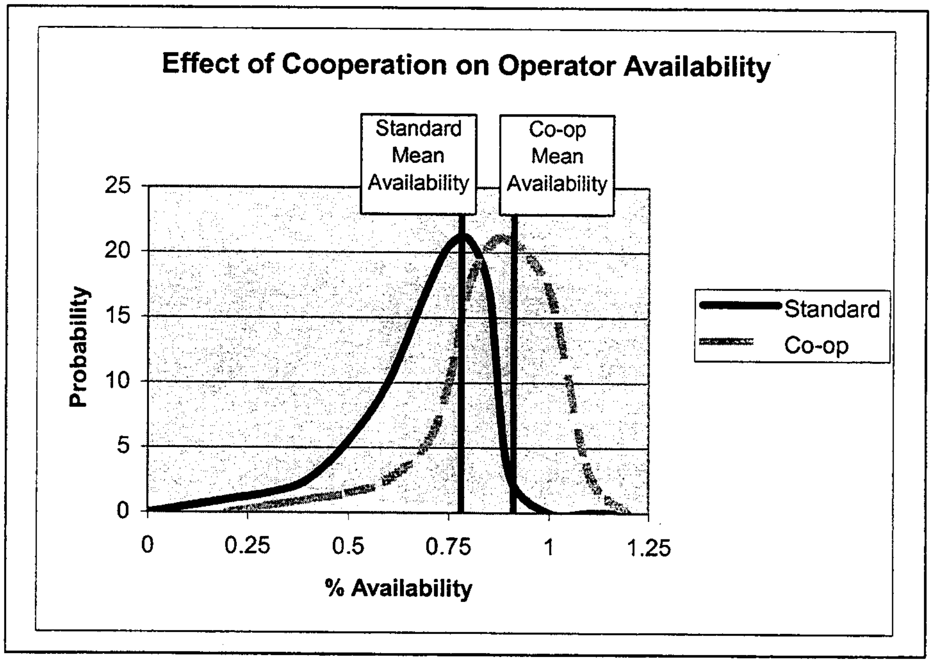


FIGURE 8.14: TREND ANALYSIS ILLUSTRATING THE EFFECT OF COOPERATION ON OPERATOR AVAILABILITY

The task time with respect to "attitude" graph was divided into three zones: good, moderate and bad. The deterministic zones for this analysis are shown in Figure 8.15.

There is no direct mathematical relationship to determine value of the attitude coefficient a_3, but a framework can be developed to illustrate the various influences. This is summarized in Table 8.7. It is assumed that the operator availability and performance is by choice (or not influenced by external circumstances or lack of skills).

Obviously, poor performance coupled with low availability will have a large influence on the amount of time and the number of repetitions to achieve proficiency; hence, a large value for a_3. But even good attendance coupled with a poor attitude will have a large impact on the learning curve.

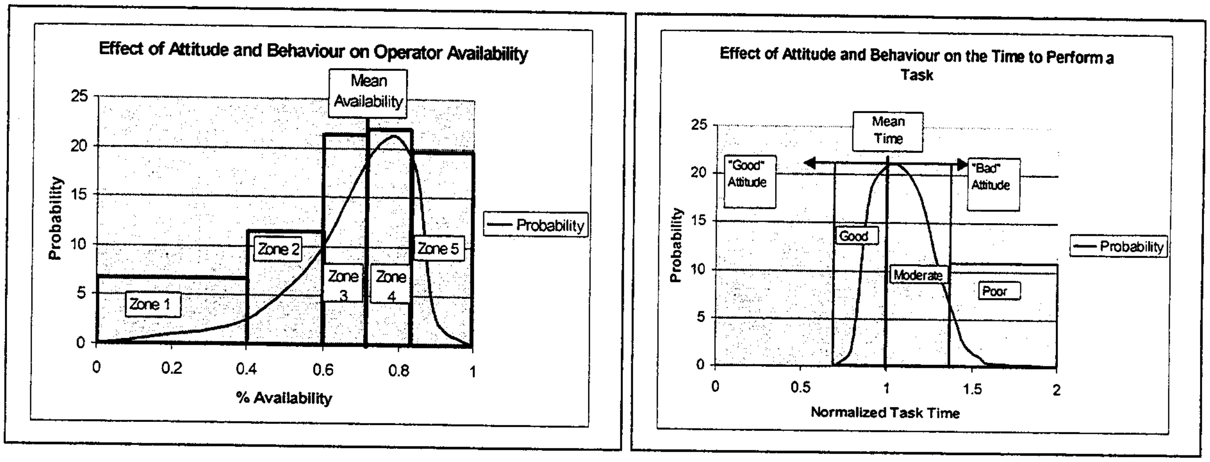


FIGURE 8.15: KNOWLEDGE BASE CONSIDERATIONS FOR ATTITUDE

On the opposite end of the scale, someone or a team with a good attitude and good attendance will achieve proficiency much quicker on the relative scale so this coefficient will have little influence on the learning curve as compared to others. In general, it is assumed that a "saw tooth" curve would result based on the conditions to generate a value of the attitude coefficient a_3. The values of a_3 in Table 8.7 are relative, and are used for illustration purposes.

Availability	Performance	Relative Value of a_3		Comment
Zone1	Poor	High	10	Considerable influence with this factor in order to attain proficiency
Zone2	Poor		9	High influence of this parameter to attain proficiency
Zone3	Poor		7	High influence of this parameter to attain proficiency
Zone4	Poor		6	Moderate influence of this parameter to attain proficiency
Zone5	Poor	Medium	5	Moderate influence of this parameter to attain proficiency
Zone1	Moderate	Medium High	7	High influence of this parameter to attain proficiency
Zone2	Moderate		6	High influence of this parameter to attain proficiency
Zone3	Moderate		3	Moderate influence of this parameter to attain proficiency
Zone4	Moderate		2.5	Moderate influence of this parameter to attain proficiency
Zone5	Moderate	Medium Low	2	Little influence with this factor in order to attain proficiency
Zone1	Good	Medium	6	Moderate influence of this parameter to attain proficiency
Zone2	Good		5	Moderate influence of this parameter to attain proficiency
Zone3	Good		2.5	Little influence with this factor in order to attain proficiency
Zone4	Good		1	Little influence with this factor in order to attain proficiency
Zone5	Good	Low	0	Little influence with this factor in order to attain proficiency

TABLE 8.7: ATTITUDE PARAMETERS

The relative value of the a_3 coefficient, with respect to the performance and availability parameters in this analysis, is shown in Figure 8.16.

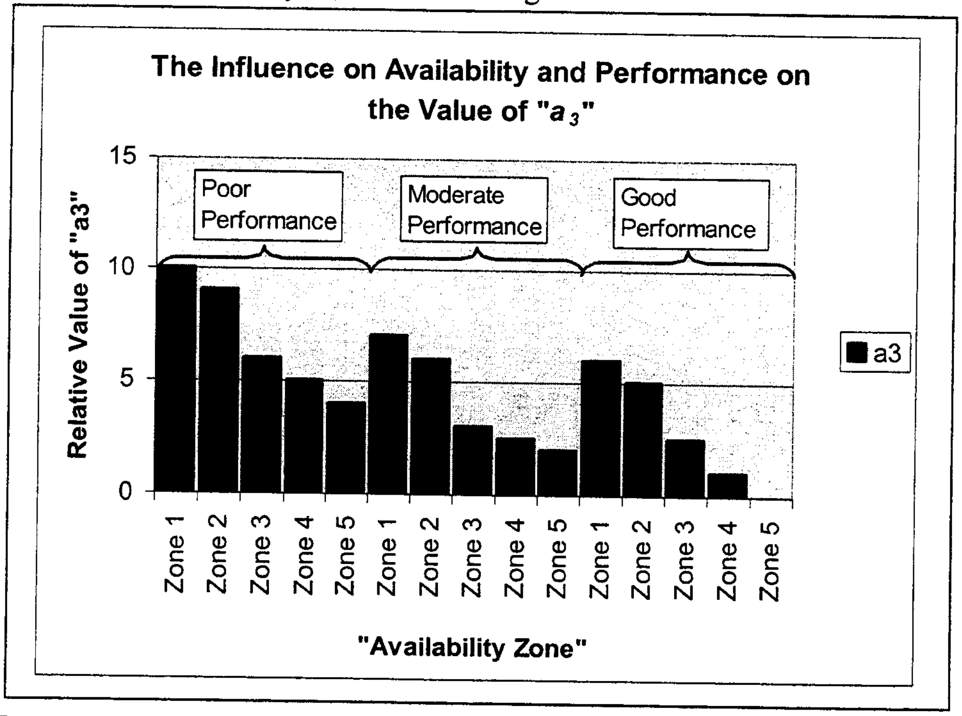


FIGURE 8.16: RELATIVE VALUES FOR THE ATTITUDE COEFFICIENT

8.2.4 Culture Coefficients

The indices that reflect the influences of the physical environment and hereditary culture, corporate culture, and peer pressure are extremely difficult to define. The quantity of employees, the demographics with respect to age, education, skill level, gender and so forth all are elements of corporate culture. The effects of each demographic on a participatory manufacturing model (or any other model) are difficult to quantify; consequently, the culture indices defined by Reuer et al [2002+] were not utilized either directly or in a modified form.

Empirically, an environment that traditionally is used to change and has a large mix of diverse hereditary cultures and backgrounds would be more accepting to change. Employees would be more willing to learn new tasks and the supporting infrastructure would be in place, while the opposite is true for a stable environment with a homogenous work force. Resistance to change (product, process or personnel) would lead to a shallower learning curve.

To determine the effect of corporate culture on the learning curve, another way of looking at the problem is required. A simple but powerful methodology is to measure and analyse various "rates of change" within a given manufacturing or corporate environment:

- the amount of small process and product changes over a specific period,
- the amount of large scale or extensive process and product changes over a specific period,
- the amount of employee turnover through attrition, resignations, or discharge over a specific period, and
- the amount of movement within the company over a specific period (departments, facilities, countries).

From the IDEF model in Appendix A, layer A2 focuses on "create the desired culture". This culture is one where communication, training, trust and cooperation exists and is rewarded. In an environment where constant modifications or introduction to new products, processes or people occurs, the employees expect change. Hence good communication and training elements typically are in place. If there is employee movement but little attrition (for any reason), then this is a reflection on the stability of the environment – which could be extended to reflect cooperation and trust. Conversely in static environments where little change occurs, cliques occur (within the various demographic categories), there is resistance to change, and the training programs may not be effective. There is less trust in the environment when there is a high attrition rate. Hence these measurables reflect directly on the static or dynamic nature of the business and can correspond to the culture coefficient a_4. For example in a dynamic environment, more employees will have a greater variety of skills. Training and support systems will be more consistent and efficient; thus, the value of a_4 will be small. This is summarized in Table 8.8. The grayed out areas represent non-common scenarios.

Small Changes	Large Scale Changes	Attrition	Employee Movement	Value of *a4*	Environment	Comment
Low	Low	Low	Low	Medium	Small family business	Very stable environment
High	Low	Low	Low	Medium Low	High volume automotive component facility – during boom period	Typical between product changeovers in large automotive facilities with dedicated equipment
Low	High	Low	Low	Medium Low	High volume automotive body and assembly facility – during boom period	More volatile environment: constant retooling or product changeovers with combination flexible and dedicated equipment
High	High	Low	Low			
Low	**Low**	**High**	**Low**	**High**	Major restructuring occurring in a facility used to a stable environment.	Negative environment: Worse case scenario for introducing product or process changes
High	Low	High	Low	Medium High	High volume automotive component facility – during slow period	Typical cycle in large automotive facilities with dedicated equipment
Low	High	High	Low			
High	High	High	Low			
Low	Low	Low	High	Medium	Typical in a company that transfers and promotes "fast track" employees	
High	Low	Low	High	Medium	Lean Manufacturing philosophy	Constant on-going improvements and training
Low	High	Low	High			
High	**High**	**Low**	**High**	**Low**	Reconfigurable Systems and Agile Mfg philosophy	Best Case Scenario for introducing product or process changes
Low	Low	High	High			
High	Low	High	High			
Low	High	High	High			

TABLE 8.8: INFLUENCES ON THE VALUE OF a_4

With the employee attrition rate being low, there is an inverse relationship between the rate of small scale and large scale changes with the value of a_4. This is shown in Figure 8.17. In environments that encourage continuous changes, change is considered the "status quo", reducing the influence of this factor in the participatory manufacturing model.

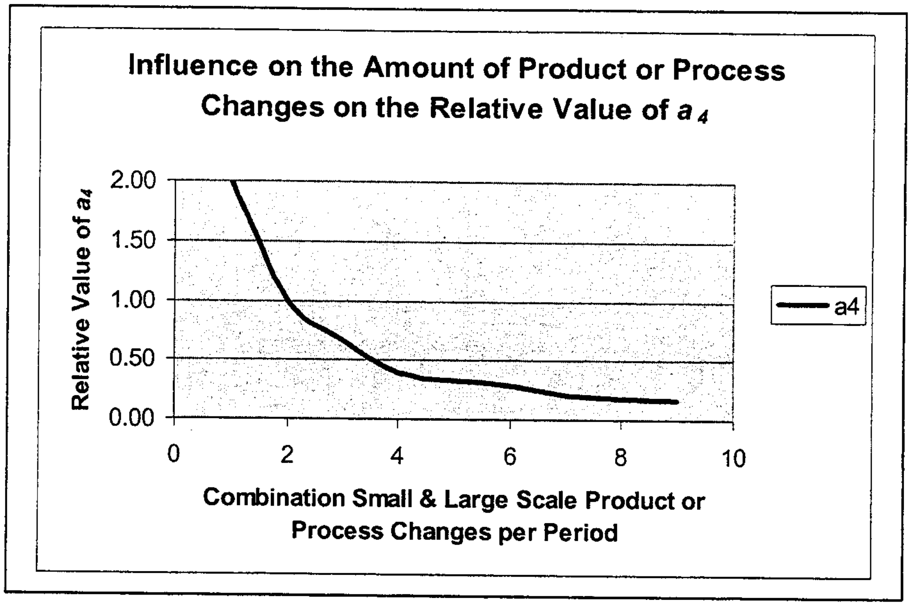


FIGURE 8.17: INFLUENCE OF PRODUCT OR PROCESS CHANGES ON THE VALUE OF a_4

There is a direct relationship between attrition with the value of a_4 – increasing the attrition rate increases a_4. Employee movement adjusts the value of a_4 – it inflates the influence of the attrition factor, as shown in Figure 8.18.

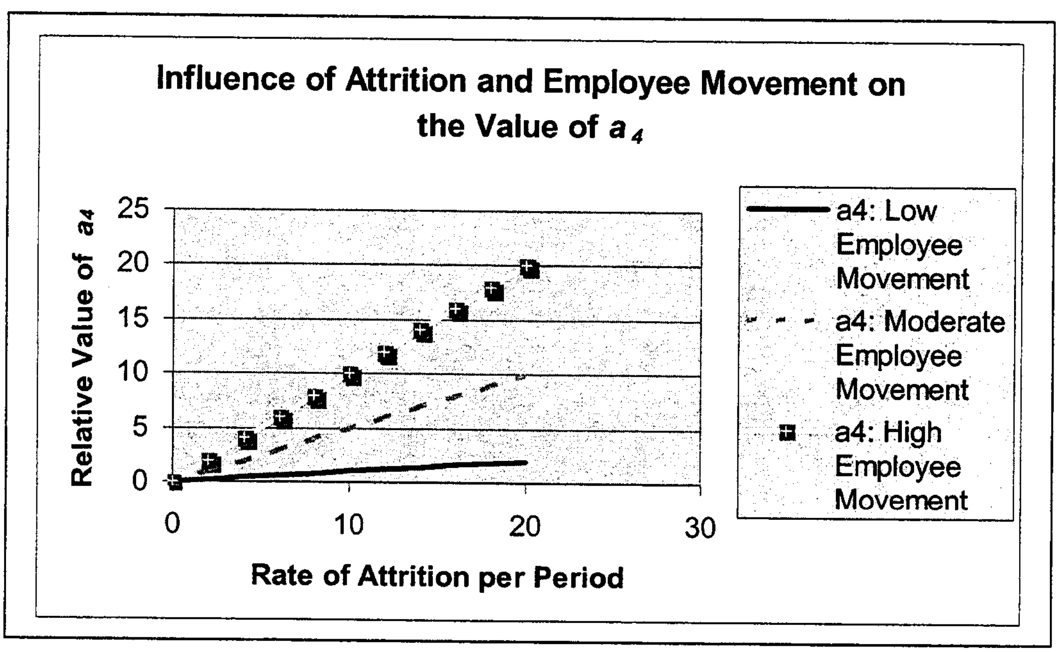


FIGURE 8.18: INFLUENCE OF ATTRITION AND EMPLOYEE MOVEMENT ON THE VALUE OF a_4

The impact of attrition is significantly greater on the culture coefficient a_4 than the impact based continuous product or process related changes; this influenced the selection of relative values chosen in Figures 8.17 and 8.18. In an environment in constant "personnel flux", changes would be assumed to threaten the well being of the employees. This increases the reluctance to initiate change; consequently, increasing the amount of time or repetitions to "learn".

The final value of the culture coefficient a_4 consists of a combination of these two factors: the tangible changes based on product or process changes and personnel related changes. Consistent with the other coefficients, a lookup table or expert system with appropriate rules is required to generate a value of the culture coefficient a_4.

The physical environment must also be considered. These elements consist of: the quantity of employees, the physical conditions, and fatigue. The larger the employee base, the more inertia there is in the system. When large scale makeovers occur, not only are employees learning new skills or acquiring information, they are learning to deal with unanticipated issues or may be revising techniques. This information must be communicated – the larger the employee base, the longer it takes to communicate undistorted information; hence, the larger the value of a_5 will be. The more extreme the physical conditions (high heat, poor lighting, constant physical motion, and so forth), more repetitions are required to achieve proficiency, increasing the value of a_5.

Typically some method of overtime will be scheduled if the accumulated production volume is less than desired. Consequently after a period of time, the learning rate will be reduced due to a fatigue factor. This introduces a piece-wise learning curve into the model. For the sake of simplicity, a fatigue factor should be considered constant.

Table 8.9 contains a summary of the factors and the influence on the value of a_5. The relative value of a_5 with respect to the factors in Table 8.9 is illustrated in Figure 8.19. A lookup table or expert system with appropriate rules is required to generate a value of the culture coefficient a_5.

# of Employees	Physical Environment	Fatigue	Relative Value of *a5*	Comment
1-20	Poor	Low	2	
21-100	Poor	Low	3	
100-300	Poor	Low	4	
>300	Poor	Low	5	
1-20	**Good**	**Low**	**0**	**Little influence of size and environment on learning curve**
21-100	Good	Low	1	
100-300	Good	Low	2	
>300	Good	Low	3	
1-20	Poor	High	7	
21-100	Poor	High	8	
100-300	Poor	High	9	
>300	**Poor**	**High**	**10**	**Long learning curve**
1-20	Good	High	5	
21-100	Good	High	6	
100-300	Good	High	7	
>300	**Good**	**High**	**8**	**Major product changeover for a Body and Assembly plant**

TABLE 8.9: INFLUENCE OF SIZE AND ENVIRONMENT

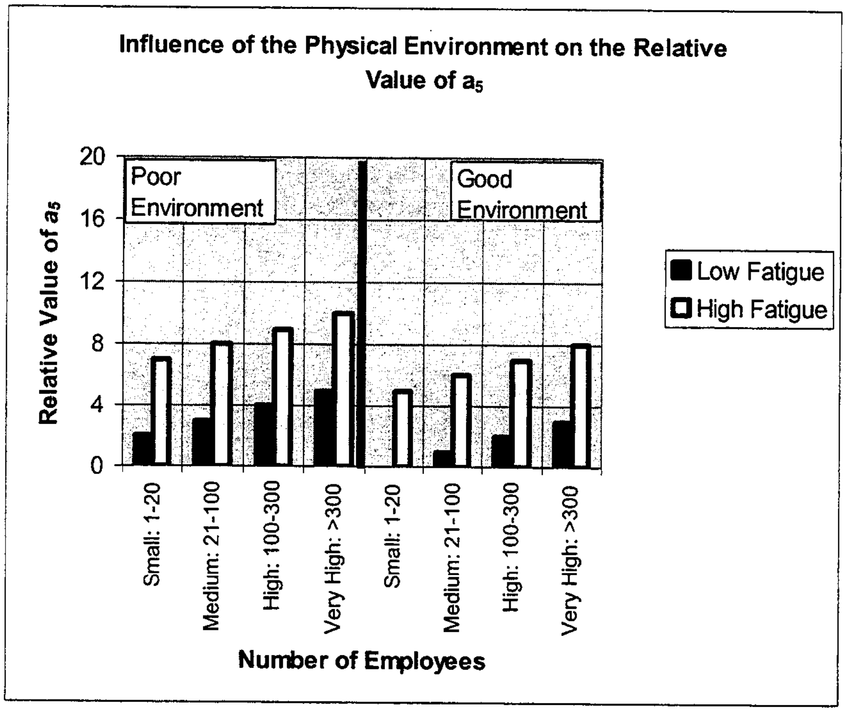


FIGURE 8.19: INFLUENCE OF FACTORS ON THE CORPORATE CULTURE COEFFICIENT *a5*

8.3 Applications

Let us apply these theories and parameters to an example from an actual case study as described below:

- Engineering students in a medium volume assembly job
- Assemble and test a power supply on a CRT monitor – 350 per 8 hr shift
  - 2.73 minute cycle time
- 2 parallel lines: 3 people per line
  - "skilled" employees can perform the tasks within 2.00 minutes
- No process related tasks: a static environment with no moving equipment
- Power roller conveyors between work cells

There are four basic tasks associated with one product feature in this work cell: material handling, assembly, visual inspection and test.

8.3.1 Tasks

The material handling task consisted of:

- Opening the package containing the CRT monitor (four per skid).
- Placing the CRT monitor face down on the assembly pallet (approximately 25 lbs in weight).
- Stacking the empty boxes on an out-going skid.
- Opening the package containing the power supplies (36 per package).
- Stacking the empty boxes on an out-going skid.

The assembly task consisted of:

- Aligning the socket on the underside of the power supply onto four easily flexed pins on the back of the CRT monitor (blind job).
- Inserting and tightening two screws to the required torque levels.
- Pluging in four wires from the back of the CRT monitor into the power supply.

The visual inspection task consisted of:

- Visual quality checks, i.e. capacitors in place.
- Writing up any anomalies.
- Loading the reject CRT monitors onto the reject trolley.

The testing tasks consisted of:

- Powering up the CRT terminal and check the test pattern.
- Performing a "cold solder joint test" via a physical impact (hammer blow).
- Writing up any anomalies.
- Loading the reject CRT monitors onto the reject trolley.
- Orienting the pallet on the conveyor, and sending it to the next work cell station.

The information entropy and the diversity values are shown in Table 8.10:

The five basic skills for each parallel line are:

- Good written and oral communications → 1 person required.
- Good physical strength, and endurance and to perform the material handling → 2 people required.
- Good physical strength, and dexterity to perform the power supply assembly operation → 2 people required.
- Training and knowledge acquisition with respect to the quality checks and the testing procedures → 2 people required.
- Excellent physical strength to load the CRT monitors onto upper shelves of the Quality Control (QC) trolley → 1 person required.

There is only one process related feature to be considered for the operational coefficient. This analysis is tabulated in Table 8.11.

Description	Number	Diversity
Material Handling		
Opening the package containing the CRT terminal (four per skid).	1	1
Place CRT face down on the assembly pallet (approximately 20 lbs in weight).	1	1
Stack empty boxes on an out-going skid.	2	1
Open the package containing the power supplies (36 per package).	1	1
Assembly		
Align the socket on the underside of the power supply onto four easily flexed pins on the back of the CRT terminal (blind job).	1	1
Insert and tighten two screws to the required torque levels.	2	1
Plug in four wires from the back of the CRT terminal into the power supply.	4	1
Visual Inspection		
Visual quality checks, i.e. capacitors in place.	8	3
Testing		
Power up the CRT terminal and check the test pattern.	1	1
Perform a "cold solder joint test" via a physical impact (hammer blow).	1	1
Write up of any anomalies.	2	1
Stack reject monitors on roller trolley	2	
Orient the pallet on the conveyor, and send to the next work cell station.	1	1
Total	**27**	**14**
$\boldsymbol{H}$	**4.75**	
$\boldsymbol{D_{R,process}}$		**0.52**

TABLE 8.10: ASSEMBLY TASKS – INFORMATION ENTROPY, DIVERSITY AND OPERATIONAL COMPLEXITY

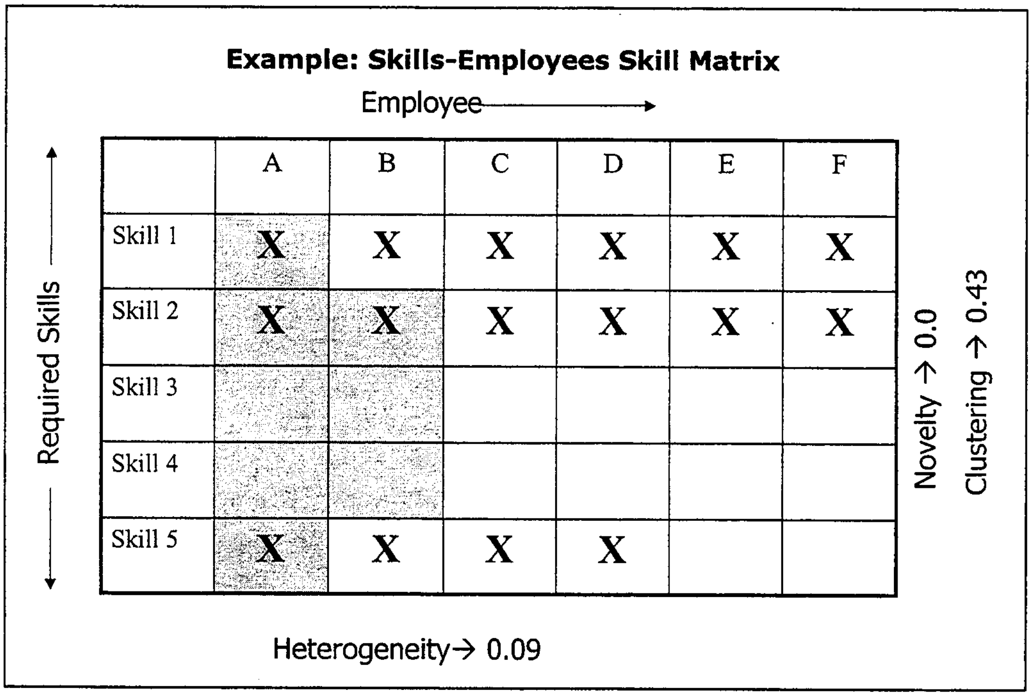
Description	Physical J = 5							
	Number	Physical Environment			Labour			
		Temp/Noise	Cleanliness	Envelope	Strength	Dexterity	SUM	D/J
Communications	0.05	0	0	0	0	0	0	0.00
Physical Strength (Material Handling)	1	0	0	0	0.5	0	0.5	0.10
Physical Strength and Dexterity (Assembly)	4	0	0	0.5	0.5	0.5	1.5	0.30
Quality Checks	2	0	0	0	0	0.5	0.5	0.10
Loading the reject trolley	0.05	0	0	0.5	1	0.5	2	0.40

Description	Cognitive Elements K = 2				
	Number	Cognitive			
		Procedures	Order of Operations	SUM	D/J
Communications	0.05	0.5	0	0.5	0.25
Physical Strength (Material Handling)	1	0	0	0	0.00
Physical Strength and Dexterity (Assembly)	4	0	0.5	0.5	0.25
Quality Checks	2	0.5	0	0.5	0.25
Loading the reject trolley	0.05	0	0	0	0.00

	Number	Task Complexity	Total
Communications	0.05	0.13	0.00
Physical Strength (Material Handling)	1	0.05	0.01
Physical Strength and Dexterity (Assembly)	4	0.28	0.15
Quality Checks	2	0.18	0.05
Loading the reject trolley	0.05	0.20	0.00
Operational Complexity	7.1		0.21
Note: 0.05 tasks --> does not occur every cycle			

TABLE 8.11: OPERATIONAL COMPLEXITY EFFORT ANALYSIS

Figure 8.20 and 8.21 illustrate the scenarios with respect to the skill sets: the shaded areas represent the basic required skill sets (which could be distributed amongst any combination of employees), the cells marked with an "X" illustrate the actual skill sets of the students starting the job.



	A	B	C	D	E	F
Skill 1	X	X	X	X	X	X
Skill 2	X	X	X	X	X	X
Skill 3						
Skill 4						
Skill 5	X	X	X	X		

FIGURE 8.20: ASSEMBLY EXAMPLE SAMPLE SKILLS MATRIX

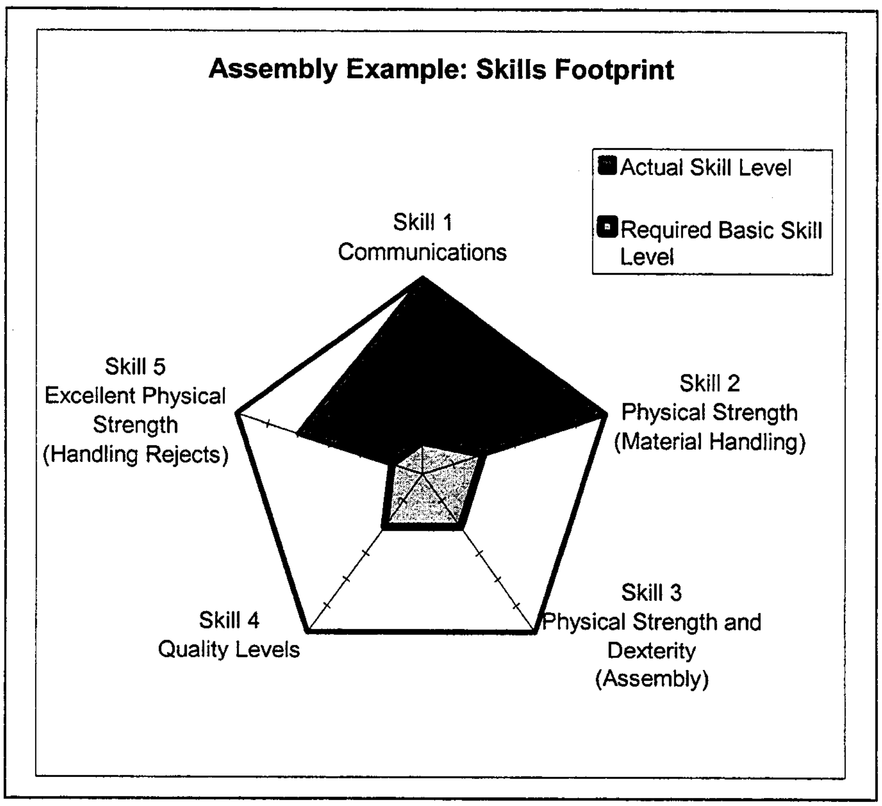


FIGURE 8.21: SKILLS FOOTPRINT FOR ASSEMBLY EXAMPLE

The cognitive and physical abilities of the engineering students are high, which corresponds to a "chunking level" of 3.17. Using the value of H from Table 8.10 and equation 8.4:

$$Factor_{cognitive} = H - \log_2 Chunking + a_0 * S_N \tag{8.4}$$

$$Factor_{cognitive} = 4.75 - 3.17 + a_0 * S_N$$

8.3.2 Determination of the Coefficients

The coefficients need to be determined from experimental data as there are many sensitivities. For this example, the values are generated from the utility charts presented in the previous section.

8.3.2.1 Skills Coefficient

For the basic requirements, the skills indices for the 5x6 skills-employee matrix are: S_N = 0.0, and $S_H + S_C = 0.52$. For the actual skill levels, the skills indices are: $S_N = 0.58$, and $S_H + S_C = 0.61$.

The effort to learn the skills is low, and the amount of employees required to learn the skills is low: let $a_0 = 0.05$* weighting factor. Assume the weighting factor is the number of skills times the numbers of employees (30), as techniques need to be learned by all the new employees for all the required skill sets; therefore, $a_0 = 0.15$.

Let the skills coefficient $a_1 = 0.75$ * (weighting factor). Again, the weighting factor is based on the skills-employee matrix: here assume the weighting factor is the square root of the number of employees times the number of skills. A direct scalar multiple as used for a_0 would over inflate the effect of this factor. For this example, the value of the weighting factor is 5.4; consequently, $a_1 = 3.18$.

8.3.2.2 Task Coefficient

For the task coefficient, the task factors must be considered. The cycle time is 2.72 minutes. The task time (once proficient) is 2.00 minutes. In general, there is a 1:1 ratio of tasks per cycle, which is a high frequency situation. From equations 8.8 and 8.9: *Task Factor*$_1$ = 0.73 and *Task Factor*$_2$ ~1; therefore, let $a_2 = 1.5$.

8.3.2.3 Attitude Coefficient

The students were available 82–100% of the time, which puts them in "Zone 5" of the "availability" utility chart. The generate attitude was "moderate"; let the attitude coefficient $a_3 = 2.0$.

8.3.2.4 Culture Coefficients

The interval for the rate of change is assumed to be one year. There were two process changes in the four month time period: an automated material handing system was introduced which eliminated two jobs per line, but was introduced in a step wise manner. One job was eliminated when the new material handling system was initiated, and another job was eliminated once the system was perfected. The redundant employees were moved into another department. The process change rate is: two in four months, or six per year; the employee movement rate was four people in four months or twelve per year. There was no attrition, only movement. Based on this, let the culture coefficient $a_4 = 0.5$.

The physical environment was clean, well lit, with comfortable temperature and humidity levels. Fatigue was not an issue – no overtime work was performed. There were less than twenty employees in the work cell and general area (including supervision, maintenance, quality and engineering representatives); consequently the value of a_5 = 1.0.The coefficients are summarized in Table 8.12.

Coefficient	Value	Comment
a_0	1.50	Low relative effort, small group of people to learn skills
a_1	3.18	All job related skills must be learned
a_2	1.00	Highly repetitive direct tasks
a_3	2.00	High availability, moderate level attitude to work
a_4	0.50	Environment of continuous change, but not at employees' expense
a_5	1.00	Comfortable working environment with moderate physical intensity

TABLE 8.12: PARTICIPATORY MODEL COEFFICIENTS' SUMMARY FOR THE ASSEMBLY EXAMPLE

For the first time the tasks were performed or $p_t(1)$, the cycle time was three times longer than the desired cycle time, so this parameter does not need to be estimated. But what is the function and value for n, and the number of cycles to become proficient?

From a "common sense" perspective for this model, the skills and tasks coefficients should be considered together and the attitude and culture coefficients should be considered together. In general, because the attitude is "good" and the students wished to learn, it is assumed that there is no significant inter-dependency between attitude, skills and tasks. However, before choosing this as a final model format, it must be tested against other formats. The various models, the values of n, i and the length of time to become proficient are presented in Table 8.13.

	$\boldsymbol{Factor_{cognitive}}$ =	2.45	$D_R + c_{o,product}$ =	0.73
	$\boldsymbol{(D_R + c_{o,product})*Factor_{cognitive} = 1.78}$			
	X_{factor}			
	1	2	3	4
	Summation Model	Scaling Model	Clustered	
	$(a_1+a_2+a_3+a_4+a_5)$	$(a_1*a_2*a_3*a_4*a_5)$	$(a_1*a_2)+(a_3*a_4*a_5)$	$(a_1+a_2)*(a_3+a_4+a_5)$
The weighting factor, X_{factor}	7.68	3.18	4.18	5.18
The learning index, n	-0.0730	-0.1764	-0.1342	-0.1083
The number of repetitions, i	3408684	507	3594	25474
The cumulative learning time (weeks)	4167.6	0.70	4.70	32.38

TABLE 8.13: RESULTS SUMMARY FOR VARIOUS PARTICIPATORY MANUFACTURING MODELS FOR THE ASSEMBLY EXAMPLE

The number of repetitions to become proficient, *i-critical* was calculated from:

$$i - critical = 10^{\frac{\log p_t(1)}{n}} \tag{8.10}$$

The cumulative time is the integral of the learning curve model. The lower limit is 1 (representing the first task or part), the upper limit is the integer value generated from equation 8.10, which represents the number of repetitions to become proficient.

$$Cumulative\ Time = p_t(1) \int_{1}^{i-critical} i^n di \text{ or} \tag{8.11a}$$

$$Cumulative\ Time = p_t(1) \left. \frac{i^{(n+1)}}{(n+1)} \right|_{1}^{i-critical} \tag{8.11b}$$

For the different model configurations, the values of the learning index varied from –0.073 to –0.176. Although there is not much difference in the magnitude of these values themselves, as exponents they influence the learning curve results significantly. The value of the learning index n is sensitive to the third decimal place.

A model which sums or multiplies all the values is the least accurate. Model 1 inflates the value of n when the values of the coefficients are low, and attenuates the value of n when the values of the coefficients are high. The opposite extreme is represented in model 2. If the coefficient values were higher, they would be inflated, and with low coefficient values the value for n is attenuated. Here, the sensitivity of model 1 is extremely high; changing the coefficient values in the third decimal place distorted the results significantly. The sensitivity of model 2 is low. Changing the values of the coefficients had little effect.

The "clustered" model 3 provided the most reasonable results. The actual learning period was approximately 3–4 weeks. Model 3 implies that skills and tasks are interlinked, and attitude and culture are interlinked. Changing the coefficient values by 10% generated a time range between 3 – 5 weeks. Model 4 was used to test an "opposite" combination of mathematical influences. If there were attitude or corporate culture issues, another model might be appropriate – one that has attitude as a factor in conjunction with the tasks as well as the corporate culture, e.g., $a_1+ (a_2*a_3*a_4*a_5)$. This was not presented, as the numerical value of this model is identical to model 3.

8.4 Summary and Conclusions

A model that ties in the elements of "operational complexity" to a participatory manufacturing model has been achieved through utilizing the learning curve phenomenon. The model directly takes into consideration memory and problem solving abilities. As well, the model also contains a weighting factor based on:

- the available skill sets of the employees,
- task factors such as time duration and direct and indirect tasks,
- attitude and behaviour and finally,
- the corporate culture and environment.

The unique approach to analysing skills, tasks, attitude and culture presents relevant metrics that are based on readily available data, and have little political context.

The skills indices reflect the novelty, heterogeneity and clustering of the skill sets within the employee base.

Considering the task metrics individually and compared to cycle time and number of cycles indirectly addresses "relearning". Intuitively, the amount of repetitions until proficiency is achieved will increase if interruptions constantly occur, or there is a long interval between performing tasks. The task coefficient a_2 reflects the relearning aspect.

Creating a model that analytically describes attitude and behaviour is beyond the scope of this work; however, the results of "good" and "bad" attitude can be represented by measureables such as operator availability and task performance. Cooperation and conflict have also been represented in this manner. The attitude coefficient, a_3, links an attitude factor to the participatory manufacturing model.

The traditional method of analysing culture focuses on demographics. This method of analysing data does not directly assist in generating a link into the participatory manufacturing model, and essentially produces irrelevant information. A fresh approach is taken in this work: using various rates of change within the workplace as a complement to the learning curve model, as the learning curve models adaptation to change. ***This simple approach is exciting, as it presents relevant metrics that are easily measured and are apolitical.***

The size and the physical environment are also considered in this framework. The larger the employee base and the more aggressive the environment, the longer it will take to achieve proficiency. This also needs to be considered in the model.

The focus of this research is creating a ubiquitous framework as opposed to simplistic absolute values when developing these metrics, as "everything is relative". A large-scale change in an automotive facility may consist of over $100 million dollars, while for a sub-supplier the figure may be in the order of $500,000 dollars.

All the weighting factor coefficients have been considered in a "relative basis" in this research. In order to be more effective, the coefficients and the weighting factor model for X_{factor} need to be coupled with experimental data and a series of sophisticated heuristics, rules and probability curves or fuzzy logic. This lends itself to an AI application, but will not be explored here.

This research has produced a solid framework on which to build sophisticated systems analysis tools that focus on realistic factors within the manufacturing environment:

- Information quantity, diversity and content
- Complexity (product, process and operational)
- Task Effort
- Employee skill sets
- Nature of the required tasks within the environment
- Attitude and Behaviour
- Corporate Culture

A methodology has been created that links product complexity to process complexity and operational complexity. This in turn has been incorporated into the learning curve model. The generic metrics provide insight into the product "manufacturability", employees' skills, and the work environment.

Utilizing the "systems approach" and analysis tools such as IDEF0 modelling and utility curves provided tremendous insight both into the problem, and generating a robust framework for the solution. This research should be extended, as tools developed here can be expanded upon and used with other concurrent engineering tools in the workplace.

9.0 CONCLUSIONS

Modelling participatory manufacturing systems is a rich topic of research that has yet to be mined. There are many aspects to be considered even with just creating a framework skeleton, let alone fleshing it out. It is overwhelming when considering each element piecemeal because of the intangible nature of the problem; however, embracing a systems approach led to the development of a framework that should serve as a basis for future work. Factors influencing the human interactions within any manufacturing system are constant: product diversity, complexity, attitude, corporate culture, etc.

A matrix methodology was developed to assess the three levels of manufacturing complexity: the product, process and operations. The systematic approach has lead to the development of an objective measure of complexity, which can be used to "mathematically" show tradeoffs at each level.

The matrix methodology used to determine the product and process complexity coefficients should be extended into a comprehensive set of lookup tables or a database to cover the various influences of tolerances, shape, material, test specifications and various processing techniques in a consistent manner. Weighting factors should also be incorporated: certain factors have a greater influence on complexity than other factors. In this research, each factor was considered of equal importance.

The quantity of information measure only considers the absolute amount of information that is available. However, an "information quality" factor should be introduced. Graphical aids and standardized terms assist people in perceiving and processing information more readily.

It would be interesting to balance standardization with fool proofing. It is common to design "fail safe" features in a product or process to ensure robust quality. But this introduces more information into a system; hence, it takes longer for people to learn all the variations. How do these counteracting influences balance out?

When determining the relative effort, each facet was assumed to be equally important. In reality, certain elements have much more influence on effort than other factors. Ranking factors were used for physical and cognitive elements when determining effort coefficients. This technique is simple and relatively objective, but it is limited to discrete values, and is only objective within its environment. An alternate method using the Human Model Processor format (e.g. dial caliper versus plug gauges) would provide a relationship based on the task time. Normalizing all tasks based on the longest task time would provide a more objective effort coefficient, as the ranking factors are continuous values that are environment independent.

Indices were developed to determine the influence of inconsistent skill sets amongst the employees, task time and corporate culture. Measuring the various rate of change in a particular setting is an objective, simple, effective and non-political method of analyzing corporate culture.

The learning curve model is an observed phenomenon. It is an effective method of linking the various influences in one model. A framework was presented that ties the operational complexity with skill levels, tasks, attitude, and corporate culture with the learning curve. The appropriate selection of model of the learning index n, and the various coefficients must be further investigated. Similar to the charts and graphs for fluid and thermodynamic coefficients, experimental data must be gathered to determine the "exact" relationships. This model validation needs to be performed, as the learning index n is sensitive to the third decimal place. Once there is confidence in the "time" element of the participatory model, it can be extended into the realm of cost and quality.

The participatory learning curve model should be introduced into discrete simulations to be able to predict the launch curve for a major product or process change. The learning curve model for each discrete area should be used in conjunction with machine failure and repair models, buffering and material handling assumptions in order to be able to determine an aggregate learning curve.

Because of the variable nature of the factors researched in this work, it is evident that an expert system using rules, probability curves, and fuzzy logic techniques in combination with experimental data would be effective approach to addressing several of the outstanding issues. Lookup tables, databases and expert systems containing valid data and rules must be developed for the various manufacturing technologies, business strategies, organizational structures and so forth.

This is an exciting topic of research, and the potential for applications as a design aid is immense.

BIBLIOGRAPHY AND REFERENCES

Ahanotu, N. D., 1998; "A Conceptual Framework for Modelling the Conflict between Product Creation and Knowledge Development Amongst Production Workers", Journal of Systemic Knowledge Management, url: http://www.tlainc.com/article9.htm

Ahlström, L. M., 2001; "An Approach to Sustainable Progress in Organizations", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Allen, B., 2001; "Cost Allocation for Process Planning in Reconfigurable Manufacturing", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Amico, M., Bruccoleri, M., Lo Nigro, G., Noto LaDiega, S., 2001; "A Set of Optimization Models for Making Investment Decisions in Manufacturing Enterprises", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

ARMMS: Agile Reconfigurable Manufacturing Machinery Systems, Anonymous, 1999, url: http://www-users.aston.ac.uk:880/mechex/armms/users/www/Web_Site/Index.htm

Baddeley, A., 1998; "Working Memory", Life Sciences, Vol. 321, pp. 167-173.

Baddeley, A., 1998; "Recent Developments in Working Memory", Current Opinion in Neurobiology, Vol. 8, Issue: 2, pp. 234-238.

Baldes, S., 2000; "Literature Survey about Personality and Emotions", Electronic E-text, url: http://www.dfki.de/~baldes/rocco/personality/personality.html

Baron, S., Dana S. Kruser, D. S., Messick Huey, B., (Editors), 1990; "Quantitative Modeling of Human Performance in Complex, Dynamic Systems", National Research Council, ISBN: POD316, url: http://www.nap.edu/books/030904135X/html/

Batavia, P. H., 1999; "Driver-Adaptive Lane Departure Warning Systems", PhD Dissertation, The Robotics Institute, Carnegie Mellon University, url: http://www-2.cs.cmu.edu/~parag/research/papers/thesis.pdf

Baum, M., 1995; "Revised ATP Program Targets: R&D for Reconfigurable Discrete Manufacturing Systems", National Institute of Standards and Technology - Advanced Technology Program, url: http://www.atp.nist.gov/www/press/tn6014.htm

Birla, S., Faulkner, D., Sorenson, S., Michaloski, J., Weinert, G., Yen, J., 2001; "Reconfigurable Machine Controllers Using the OMAC API", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Bongaerts, L., 1998; "Integration of Scheduling and Control in Holonic Manufacturing Systems", PhD Dissertation, Katholieke Universiteit Leuven, url: http://www.mech.kuleuven.ac.be/~lbongaer/pubs.html

Bonvik, A. M., 1999; "How to Control a Lean Manufacturing System", Copyright © Massachusetts Institute of Technology 1996, 1999, url: http://web.mit.edu/manuf-sys/www/amb.summary.html

Boeree, G. C., 1997; "Personality Theories", Electronic E-text, Copyright © Shippensburg University 1997, url: http://www.ship.edu/~cgboeree/perscontents.html

Buffa, E. S., 1983; "Modern Production/Operations Management – 7/e", John Wiley and Sons.

Bull, K. S., 2001; Psychology Course Notes for EPSY 5463, "Psychology of Learning", Electronic E-text, Oklahoma State University, url: http://home.okstate.edu/homepages.nsf/e06a860dccf8ff9386256874007f07d0/89df3a3a7f2e76148625680a0062274b!OpenDocument&Highlight=0,epsy

Burns, R., 1997; "Intelligent Manufacturing", Aircraft Engineering and Aerospace Technology, Volume 69, No. 5, pp. 440 – 446.

Busse, D. K, Johnson, C. W., 1998; "Modeling Human Error within a Cognitive Theoretical Framework", Proceedings of the 2nd European Conference of Cognitive Modeling (ECCM-98), pp. 90-97, url: http://www.dcs.gla.ac.uk/~bussed/ics/ics_reason1.html

Busse, D. K., Johnson, C. W., 1999; "Identification and Analysis of Incidents in Complex, Medical Environments", Proceedings of the 1st Workshop on Human Error and Clinical Systems, url: http://www.dcs.gla.ac.uk/~johnson/papers/HECS_99/Busse_Johnson.htm

Campbell, G. E., Cannon-Bowers, J. A., 2000; "The Application of Human Performance Models in the Design and Operation of Complex Systems", Naval Air Warfare Center Training Systems Division, url: http://www.manningaffordability.com/s&tweb/PUBS/AppHumPerfModelDesign/AppHumPerfModelDesign.htm

Canas, J. J., Antoli, A., 1998; "The Role of Working Memory in Measuring Mental Models", 9th European Conference on Cognitive Ergonomics, pp. 139-144, url: http://www.cs.vu.nl/~eace/ECCE9/papers/canas.pdf

Cannon-Bowers, J. A., 2000; "A Strategic Framework for Human Systems Integration in 21st Century Naval Warfare Training Systems", Naval Air Warfare Center Training Systems Division, url: http://www.manningaffordability.com/S&tweb/PUBS/StratFrmwkHumSysInt/StratFrmwkHumSysInt.htm

Cattell, R. B., Eber, H. W., Tatsuoka, M. M., 1970; "Handbook for the Sixteen Personality Factor Questionnaire", Champaign, IL, Institute for Personality and Ability Testing.

Chen, L., Wolf, A., 2001; "Modularization in Reconfiguration Design Theory and Methodology", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Chung, M. J., Kwon, P., Pentland, B., 2001; " Process Modeling and Reconfiguration in a Virtual Manufacturing Environment", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Colding, B., N., 2001; "A Manufacturing Execution System Applied to Intelligent Adaptive Grinding Machines", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Committee on the Effects of Aircraft-Pilot Coupling on Flight Safety, 1997; "Aviation Safety and Pilot Control: Understanding and Preventing Unfavorable Pilot-Vehicle Interactions", National Research Council, ISBN 0-309-05688-8, url: http://www.nap.edu/books/0309056888/html/index.html

Committee to Study Information Technology and Manufacturing, 1995; "Information Technology for Manufacturing: A Research Agenda", National Research Council, National Academy Press, ISBN 0-309-05179-7, url: http://www.nap.edu/books/0309051797/html/

Committee on Visionary Manufacturing Challenges, 1998; "Visionary Manufacturing Challenges for 2020", National Research Council, National Academy Press, ISBN 0-309-06182-2, url: http://books.nap.edu/html/visionary/

Cooper, W. W., Sinha, K. K., Sullivan, R. S., 1995; "Accounting for Complexity in Cost High Technology Manufacturing", European Journal of Operational Research, pp. 316-326.

Cooper, W. W., Sinha, K. K., Sullivan, R. S., 1992; "Measuring Complexity in High Technology Manufacturing: Indexes for Evaluation", Interfaces, pp. 38-48.

Corker, K. M., 1999; "Human Performance Simulation in the Analysis of Advanced Air Traffic Management", Proceedings of the 1999 Winter Simulation Conference, pp. 821–828.

Costa Jr, P. T., McCrae, R. R., 1985; "The NEO Personality Inventory", Psychology Assessment Resources.

Crisp, H., Hoang, N., Schmidt, R., 1999; "A Human Centered Design Environment for Complex Systems", Proceedings of the International Symposium of the International Council on System Engineering.

Dachtchenko, O. A., Elchov, P. E., Dachtchenko, A. I., 2001; "Some Aspects of Non-traditional Assembly Methods Application for Reconfigurable Manufacturing Systems", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Davidrajuh, R., Deng, Z., 1998; "Enabling Technologies for Information Flow in Computer Integrated Manufacturing Systems", Proceedings of the 18th AIMTDR Conference, © Narosha Publishing House, ISBN 81-7319-275-8.

Davidrajuh, R., Deng, Z., Wang, K., 1999; "Realizing Integrated Intelligent Manufacturing System with Distributed Intelligent Agents", Proceedings of the 15th International Conference on Computer-Aided Production Engineering.

Davidson, J. B., Schmidt, D. K., 1994; "Extended Cooperative Control Synthesis", NASA Technical Memorandum 4561, url: http://techreports.larc.nasa.gov/ltrs/PDF/tm4561.pdf

Davidson, J. B., Schmidt, D. K., 1992; "Modified Optimal Control Pilot Model for Computer-Aided Design and Analysis", NASA Technical Memorandum 4384, url: http://techreports.larc.nasa.gov/ltrs/PDF/tm4384.pdf

Defence Standard 00-25 (UK), 1991; "Human Factors for Designs of Equipment Part 4: Workplace Design", Issue 1 Ministry of Defence, url: http://www.dstan.mod.uk/data/00/025/04000100.pdf

Deng, Z., Davidrajuh, R., Bang, B., Laksa, A., 1999; "Multi-Agent Based Modelling for Inter-Enterprise Integration", Proceedings of the IFIP International Enterprise Modeling Conference.

Deng, Z., Petterson, J., Jensen, E. N., Bang, B., Davidrajuh, R., 2000; "Realising Inter-Enterprise Remotely Synchronous Collaborative Design and Planning within a Multi-platform Environment", International Conference on Concurrent Engineering.

Deutsch, S., 1998; "Multi-disciplinary Foundations for Multiple-task Human Performance Modeling in OMAR", 20th Annual Meeting of the Cognitive Science Society.

Doman, D. B., Anderson, M. R., 2000; "A Fixed-Order Optimal Control Model of Human Operator Response", Automatica, Vol. 36, Issue 3, pp. 409-418.

Dondeti, V. R., Mohanty, B. B., 1998; "Impact of Learning and Fatigue Factors on Single Machine Scheduling with Penalties for Tardy Jobs", European Journal of Operations Research, Vol. 105, pp 509-524.

Dove, R., 1995; "Agile Cells and Agile Production", Copyright © 1995, 1998, Paradigm Shift International, url: http://www.parshift.com/Essays/essay012.htm

ElMaraghy, W., 2001; "Systems Analysis and Design: An Approach to Information-Based Design Process Modelling", CIRP 2001 International Conference on Design in the New Economy, pp. 41-46.

Eysenck, H. J., 1972; "Psychology is about People" New York, Library Press.

Federal Highway Administration (FHWA), Anonymous, 1996; "Initial Development of a Prototype Driver Performance Model for Highway Design", FHWA-RD-96-134, url: http://ntl.bts.gov/DOCS/96134/index.html

Felciano, R. M., 1995; "Human Error: Designing for Error in Medical Information Systems", Graduate Seminar at Stanford University School of Medicine, Copyright © 1995-1997, url: http://www.smi.stanford.edu/people/felciano/research/humanerror/humanerrortalk.html

Feldman, K., Slama, S., 2001; "Highly Flexible Assembly – Scope and Justification", Annals of the CIRP, Volume 50, No. 2, pp.489 - 498.

Ferreira, J. C. E., Steele, J., Wysk, R. A., Pasi, D. A., 2001; "A Schema for Flexible Equipment Control in Manufacturing Systems", International Journal of Advanced Manufacturing Technology, Volume 18, pp. 410-421.

Fitts, P. M., 1954; "The Information Capacity of the Human Motor System in Controlling the Amplitude of Movement", Journal of Experimental Psychology, Vol. 47, pp.381-391.

Fletcher A, Dawson D., 2001; "Transportation Research Part F", Psychology and Behaviour, Vol. 4, Issue 1, pp. 75 - 88.

Gibson, F. P., Plaut, D. C., 1995; "A Connectionist Formation of Learning in Dynamic Decision-Making Tasks", Proceedings of the 17th Annual Conference of the Cognitive Science Society, pp. 512-517.

Glardon, R., Zhang, G., 2001; "An Analytical Comparison of Cost and Performance Among DMS, ASM, FMS and RMS", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Gollop, F. M., Monahan, J. L., 1991; "A Generalized Index of Diversification: Trends in U.S. Manufacturing", The Review of Economics and Statistics (73), pp. 318-330.

Grant, S., 1990; "Modelling Cognitive Aspects of Complex Control Tasks", PhD Dissertation, University of Strathclyde, Copyright © 1990, 1995, url: http://www.simongrant.org/pubs/thesis/.

Green, M., 1997; "Human Performance", Electronic E-Text for C301, University of Alberta, url: http://www.cs.ualberta.ca/~mark/c301/performance.html

Griffiths, R., 2002; "Lecture Notes Index: Human Computer Interaction Topics", Electronic E-text, University of Brighton, url: http://www.it.bton.ac.uk/staff/rng/teaching/notes/index.html

Heineman, P. L., 1995; "Temperament Theory", Copyright, url: http://pmc.psych.nwu.edu/perproj/others/heineman/history.htm

Heisel, U., Michaelis, M., 2001; "RMS – Opportunities and Challenges", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

HIPARMS, Anonymous; 2001; "HIPARMS: HIghly Productive And Reconfigurable Manufacturing System", European Commission Project Number BE98-5508, url: http://hiparms.ifw.uni-hannover.de/HIPARMS-FRAME-STARTSEITE.htm

Hiromi Ebara, H., Takahashi, K., Morikawa, K., Nakamura, N., 2001; "The Cellular Manufacturing System For Responding To Changes In Demand", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Hormozi, A. M., 2001; "Agile Manufacturing: The Next Logical Step", Benchmarking, An International Journal, Volume 8, No. 2, pp. 132 –143.

Huang, C. C., and Kusiak, A., 1998; "Manufacturing Control with a Push-Pull Approach", Int. J. Prod. Res., Vol. 36, No.1, pp 251 - 275.

Huller Hille GmbH Anonymous, 2001 Copyright, "CrossHueller: A Company of ThyssenKrupp Technologies", url: http://www.hueller-hille.com/crosshueller/ger/start.html

Huxley, A., 1978; "Brave New World", Granada Publishing Ltd.

Integrated Manufacturing Technology Initiative (IMTI), 2000, url: http://imti21.org/

Johnson, T. R., 1997; "Control in Act-R and Soar", Proceedings of the 19th Annual Conference of the Cognitive Science Society, pp. 343-348, url: http://www.sahs.uth.tmc.edu/TRJohnson/papers/CogSci97-Control-in-Act-R-and-Soar.html

Kals, H. J. J., Vos, J. A. W. M., 2001; "Flexfactory: An Assembly Process Based Concept for Configuration of Flexibly Automated Assembly Systems", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Kihlman, H., 2001; "Reconfigurable Tooling for Airframe Assembly", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Kinnander, A., Ilar, T., Eriksson, U., 1998; "Competence Requirements and Their Impact on Manufacturing System Performance", Annals of the CIRP, Vol. 47, Issue 1, pp. 385-388.

Kjellberg, A., Abestam, L., 1997; "A Human Factor Framework for Analysis of an Assembly Work", Annals of the CIRP, Vol. 46, Issue 1, pp. 377-380.

Kjellberg, A., 1999; "Teams – What's Next? From Fragmentation and Consciousness to Responsiveness by Competence Management for Modular Manufacturing Learning", Annals of the CIRP, Vol. 48, Issue 2, pp. 599-609.

Kjellberg, A., Werneman, A., 2000; "Business Innovation – Innovative Teams, Competence Brokers and Beehive Structures – in a Sustainable Work Organization", Annals of the CIRP, Vol. 49, Issue 1, pp. 355-358.

Kocsis, L., Jurak, M., Béda, G., Fehér, M., Boros, Z., Stefanik, G., Dobrev, T., Vitliemov, P., Bratanov, D., Koujoharov, V., Andonov, Y., 2000; "Analysis of the Upper Limb Motion, Impairments, and the Motion Therapies Used and Improvements Proposed for the Impairment Rehabilitation", Project N°: IST-1999-13109, Deliverable 7, Acronym: REHAROB, url: http://reharob.manuf.bme.hu/publications/d7.pdf

Koestler, A., 1989; The Ghost in the Machine, Arkana Books.

Koren, Y., Ulsoy, A. G., 2001; "Engineering Research Center for Reconfigurable Manufacturing Systems - Research", University of Michigan, url: http://erc.engin.umich.edu/research.htm

Kothiyal, K., 2002; "Ergonomics, Productivity and Safety", Electronic E-text for GENS8004, School of Safety Science, University of New South Wales, url: http://www.safesci.unsw.edu.au/gens8004/index.htm

Lehman, J., Laird, J., Rosenbloom, P., 2002; "A Gentle Introduction to SOAR, an Architecture for Human Cognition", Electronic E-text, University of Michigan, url: http://ai.eecs.umich.edu/soar/docs/Gentle.pdf

MacKenzie, I. S., 1995; "Movement Time Prediction in Human-Computer Interfaces", In Baecker, R. M., Buxton, W. A., Grudin, J., Greenberg, (Eds.), Readings in Human Computer Interaction, 2nd ed, pp 483-493, Los Altos, CA.

Maslow, A. H., Frager, R., Fadiman, J., 1987; "Motivation and Personality", 3rd edition, Addison-Wesley Pub. Co., ISBN: 0060419873.

Masood, S. H., 1996; "Intelligent Rapid Prototyping with Fused Deposition Modelling", Rapid Prototyping Journal, Volume 2, No. 1, pp. 24–33.

Matta, A., Tolio, T., 2001; "A Simulation Study of Tool Management Policy in FMS with Network Part Program", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Messick H., B., Wickens, C. D., Editors, 1993; "Workload Transition: Implications for Individual and Team Performance", National Research Council, National Academy Press, ISBN 0-309-04796-X, url: http://www.nap.edu/books/030904796X/html/index.html

Meredith, S., and Francis, D., 2000; "Journey Towards Agility: the Agile Wheel Explored", The TQM Magazine, Volume 12, Number 2, pp. 137-143 # MCB University Press. ISSN 0954-478X.

Miller, G. A., 1956; "The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information", The Psychological Review, Vol. 63, pp. 81-97, url: http://www.well.com/user/smalin/miller.html

Miltenburg, J., 1997; "Comparing JIT, MRP, and TOC, and embedding TOC into MRP, International Journal of Production Research, Vol. 35, No.4, pp 1147–1169.

Mitchell, C. M., 1996; "Models for the Design of Human Interaction with Complex Dynamic Systems", Proceedings of the Cognitive Engineering Systems in Process Control.

Molnar, M., Fernandez, R., Huff, B., 2001; "Development of a Standard Reconfigurable Assembly Cell for Agile Manufacturing", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Monfarad, R. P., Weston, R. H., 1997; "The Re-engineering and Reconfiguration of Manufacturing Cell Control Systems and Reuse of Their Components", Proceedings of the

Instn. Mechanical Engineers, Volume 211, Part B, pp. 495 – 508, url: http://msiri.lboro.ac.uk/people/Radmehr/pdf/Re-eng.pdf

Nagel, R., Dove, R., Preiss, K., 1991; "21st Century Manufacturing Enterprise Strategy – an Industry Led View", Vol. 1 and 2, Bethlehem, PA.

Neerincx, M. A., 1995; "Harmonizing Tasks to Human Knowledge and Capacities", PhD Dissertation, Rijksuniversiteit Groningen, url: http://www.ub.rug.nl/eldoc/dis/ppsw/m.a.neerincx/

Neill, J., 1999; Psychology Course Notes for Psychology 201, "Individual Differences - Unit 4311", Electronic E-text, University of Canberra, url: http://www.canberra.edu.au/uc/lectures/scides/sem992/unit4311/Lectures.html

Neugebauer, R., Ihlenfeldt, S., Weidermann, F., Kirchner J., Wieland, F., 2001; "Reconfiguration Capabilities of Single-Purpose Machine Tools based on Parallel Kinematic Structures", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Niimi, A., Sata, T., Shiramizu, K., Masuura, T., Hisada, N., 1997; "Development of the New Human Conscious Automobile Assembly Plant", Annals of the CIRP, Vol. 46, Issue 1, pp. 381-384.

Nunes, D. N. J., 2001; "Object Modelling for User-Centered Development and User Design Interface Design: The Wisdom Approach", PhD Dissertation, University of Madeira, url: http://math.uma.pt/njn/NunoPhDPrint.pdf

Onuh, S. O., Hon, K. K. B., 2001; "Integration of Rapid Prototyping Technology into FMS for Agile Manufacturing", Integrated Manufacturing Systems, Volume 12, No. 3, pp. 197 – 186.

Okuda, Y, Nakamura, Y., Kishi, M., Ishikawa, N., Hitomi, M., 1999; "Simulation of Human-Oriented Production Systems Considering Workers' Cooperation", 8th International Workshop on Robot and Human Interaction.

OSACA-Anonymous; 2000; "Open System Architecture for Controls within Automation Systems", url: http://www.osaca.org/osaca/Default.htm

Owusu, Y. A, 1999; "Importance of Employee Involvement in World-Class Agile Management Systems", International Journal of Agile Management Systems, Volume 1, No. 2, pp. 107–115.

Papazian, J., 2001; "Reconfigurable Tooling for Sheet Metal Forming", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Pedrazzoli, P., Urbani, A., Fassi, I., Molinari-Tosatti, L., Boer, C.R., 2001; "Flexibility and Reconfigurability: An Analytical Approach and Some Examples", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Polypod-Anonymous, 1997; "Locomotion with a Unit Modular Reconfigurable Robot", Stanford University, url: http://robotics.stanford.edu/users/mark/polypod.html

Psychology Course Notes for HP603 - Anonymous, 1999; "Personality", Electronic E-text, University of Ballarat, url: http://www.ballarat.edu.au/bssh/psych/hp603/603start.htm

Qiao, B., Zhu, J., 2000; "Agent-Based Intelligent Manufacturing System for the 21st Century", Proceeding from the International Forum for Graduates and Young Researchers at Expo 2000 Hannover, the World Exposition in Germany, url: http://www.shaping-the-future.de/pages/future.htm

Rasmussen, J., 1993; "Diagnostic Reasoning in Action", Systems, Man and Cybernetics, IEEE Transactions, Vol. 23, Issue 4, pp. 981 –992.

Rasmussen, J., 1988; "Human Factors in the High-Risk Systems", IEEE Fourth Conference on Human Factors and Power Plants, pp. 43–48.

Richards, J., 1999; "Functional Biomechanics in Clinic and Research", Electronic E-text, Copyright © 1999, University of Salford, url: http://146.87.28.49/book/Chapter1/

Reuer, J. J., Park, K. M., Zollo, M., 2002+; "Experiential Learning in International Joint Ventures: The Roles of Experience Heterogeneity and Venture Novelty" forthcoming, In Contractor, F. J., & Lorange, P. (Eds.), *Cooperative Strategies and Alliances*. Amsterdam, The Netherlands: Elsevier, url: http://wiscinfo.doit.wisc.edu/ciber/ideb2001/Reuer%20Article%201.pdf

Rogers, G. G., Bottaci, L., 1997; "Modular Production Systems: A New Manufacturing Paradigm", International Journal of Intelligent Manufacturing, Volume 8, No.2, pp. 147-156.

Ross, A., Xi, J., Mechefske. C., 2001; "Varying Topology of a Reconfigurable Parallel Kinematic Machine", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Ross, E. M., 1994; "The Twenty-first Century Enterprise, Agile Manufacturing and Something Called CALS", World Class Design to Manufacture, Vol. 1, No. 3, pp. 5-10, MCB University Press, 1352-3074.

Sarker, B. R., and Fitzsimmons, J. A., 1989; "The Performance of Push and Pull Systems: a Simulation and Comparative Study", Int. J. Prod. Res., Vol. 27, No. 10, pp 1715 - 1731.

Scheifele, D., 2001, "Reconfigurable Software for Open Control Systems", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Schmidt, C. F., 2001; "Cognition and Computation", Electronic E-text for 830-472, Rutgers: the State University of New Jersey, url: http://www.rci.rutgers.edu/~cfs/index.html

Sela, M. N., Gaudry, O., Dombre, E., Benhabib, B., 1997; "A Reconfigurable Modular Fixturing System for Thin-Walled Flexible Objects", International Journal of Advance Manufacturing Technology, Vol. 13, No. 9, pp. 611-617.

Shirinzadeh, B., 1995; "Flexible and Automated Workholding Systems", Industrial Robot, Vol. 22, No. 2, pp. 29-34.

Sipper, D., and Shapira, R., 1989; "JIT vs. WIP – a Trade Off Analysis, International Journal of Production Research, Vol. 27, No.6, pp. 903 - 914.

Skinner, B. F., 1974; "About Behaviorism" New York, NY: Alfred A. Knopf. Summary @ url: http://www.wabash.edu/depart/psych/Courses/Psych97A/STUDENT%20PROJECTS/Skinner/hartille/table%20of%20contents

Skinner, W., 1978; " Manufacturing in the Corporate Strategy", John Wiley and Sons.

Sheldon, W. H., Stevens, S. S., "The Varieties of Temperament: A Psychology of Constitutional Differences", New York: Hafner Publishers Co., 1942.

Smirnov A., 1999; "Constraint & Agent- Based Environment for Configuration Management of Manufacturing Systems", Studies in Informatics and Control, Informatics and Control Publications, Bucharest, Vol. 8, No. 1, pp.19-25, url: http://www.ici.ro/ici/revista/sic99_1/art02.html

St. Amant, R., Riedl, M. O., 2001; "A Perception/Action Substrate for Cognitive Modeling in HCI", International Journal of Human-Computer Studies, Vol. 55, pp. 15-39, url: http://ritter.ist.psu.edu/papers/ijhcs-em-si/stamantR01.pdf

Stroop, J. R., 1935; Studies of Interference in Serial Verbal Reactions", Journal of Experimental Psychology, Vol. 12, pp. 643-662, url: http://psychclassics.yorku.ca/Stroop/

Sugimara, N., 2000, "Holonic Manufacturing System (HMS)", 2000 Pacific Conference on Manufacturing, pp. 989– 996.

Suh, N. P., 2001; "The Principles of Design", New York, Oxford University Press.

Tichy, N. M., Sherman, S., 1993; "Control Your Destiny or Someone Else Will", HarperBusiness.

Todorov, E., 2001; "On the Role of Primary Motor Cortex in Arm Movement Control", (To appear in) Progress in Motor Control III, url: http://www-rcf.usc.edu/~etodorov/papers/MotorCortex.pdf

Toenshoff, H. K., Schnuelle, A., Drabow, G., 2001; " Highly Flexible and Reconfigurable Manufacturing Systems Due to a Modular Design", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Underdown, D. R., 1997; "An Enterprise Transformation Methodology", PhD Dissertation, The University of Texas at Arlington, url: http://arri.uta.edu/eif/dru_diss/dru_diss.pdf

U. S. Department of Defence (DoD), Anonymous, 1998; "Human Engineering Process", SC-21/ONR S&T Manning Affordability Initiative, url: http://www.manningaffordability.com/S&tweb/HEResource/Other/SEandHE.htm

Vallance, R. R., Kiani, S., Nayfeh, S., 2001; "Open Design of Manufacturing Equipment", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Van Der Veer, G.C., Hoeve, M., Lenting, B. F., 1996; "Modeling Complex Work Systems - Method Meets Reality", In Proceedings of the 8th European Conference on Cognitive Ergonomics, pp. 115--120.

Vertegaal, R., 2002; "Human-Computer Interaction", Electronic E-text for CISC325, Queen's University, url: http://www.cs.queensu.ca/home/cisc325/

Wagner, R., Castanotto, G., Goldberg, K., 1997 ; "FixtureNet: Interactive Computer Aided Design via the WWW", International Journal of Human-Computer Studies, Volume 46, Number 6, url: http://memento.ieor.berkeley.edu/fixture/Paper/wcg1-6.html

Walczyk, D. F., Hosford, J. F., Papazian, J., 2001; "Using Reconfigurable Tooling and Convective Heating for Incremental Forming of Composite Aircraft Parts", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Wang, C., 2001; "Agile Manufacturing System for Customized Artificial Joint", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Weston R. H., 1999; "Reconfigurable, Component-Based Systems and the Role of Enterprise Engineering Concepts", Computers in Industry, Special Issue: CIMOSA: CIM Open System Architecture. Evolution and Applications in Enterprise Engineering & Integration. F. Vernadat and K. Kosanke (Eds.) Vol. 40, Nos. 2-3, pp. 321-343. ISSN 0166-3615.

Wickens, C. D., Gordon, S. E., Liu, Y., 1998; "An Introduction to Human Factors Engineering", New York: Addison Wesley Longman. ISBN: 0321012291.

Wiendahl, H. P, Hernández, R., 2001; "The Transformable Factory Strategies, Methods and Examples", CIRP International Conference on Agile, Reconfigurable Manufacturing Proceedings, CD ROM.

Wimmer, M., 2000; "Designing Interactive Systems: Key Issues for a Holistic Approach. PhD Dissertation, Schriften der Johannes-Kepler-Universität Linz, ISBN: 3 85487 195 3, url: http://falcon.ifs.uni-linz.ac.at/research/mw_diss.html

Wyns, J., Van Brussel, H, Valckenaers, P., Bongaerts, L., 1996; "Workstation Architecture in Holonic Manufacturing Systems", Presented at 28th CIRP International Seminar on Manufacturing Systems, pp.220-231.

Yamada, S., Vink, P., 2000; "Organizational Aspects of Human-Machine Coexisting Systems (HUMACS)", 2000 Pacific Conference on Manufacturing, pp. 981–988.

Yamada, R., Koshimuzu, H., Tomita, H., Kaihara, T., 2000; "An Overview of IMS-HUTOP Project", 2000 Pacific Conference on Manufacturing, pp. 997–1003.

Yelle, L.E., 1979; "The Learning Curve: Historical Review and Comprehensive Survey", Decision Sciences, Vol. 10, 1979, pp. 302–328, url: http://www.decisionsciences.org/dsj/Files/10_2_302-328.pdf

Yin, J. Z., 2001; "Relating Learning Capability to the Success of Computer-Integrated Manufacturing", Technological Forecasting and Social Change, Volume: 69, Issue: 1, pp. 53-70.

Youssef, M. A., 1994; "Design for Manufacturability and Time-to-Market, Part 1: Theoretical Foundations", International Journal of Operations and Production Management, Volume 14, No. 12, pp. 6–21.

Zachman, J., 2002; "Enterprise Architecture", Copyright © 2002, url: http://www.zifa.com/frmwork2.htm

Zelinski, P., 2001; "Agile Or Lean? ", Copyright © MMS Online, url: http://www.mmsonline.com/articles/050003.html

Zhang, W. J., Bi, Z. M., 2001; "Flexible Fixture Design and Automation: Review, Issues and Future Directions", International Journal of Production Research, Vol. 39, No. 13, pp. 2867–2894.

APPENDIX A

A. 1 Body Type Theories

A.1.1 Greek Body Type Theory

Humour	**Fluid**	**Temperament**	**Character**
Choleric	Yellow bile	Warm and dry	Irritable/ excitable
Melancholic	Black bile	Cool and dry	Depressed
Sanguine	Blood	Warm and wet	Optimistic/ expressive
Phlegmatic	Phlegm	Cool and wet	Calm

TABLE A.1: FOUR GREEK HUMORS [NEILL, 1999]

A.1.2 Sheldon Body Type Theory

Body Type	**Character**	**Shape**
Ectomorph	Cerebrotonic (quiet, restrained non-assertive, somewhat withdrawn)	Fragile, lean, delicate, poorly muscled
Mesomorph	Somatotonic (active, assertive, vigorous, combative)	Predominance of musculature; muscular
Endomorph	Viscerotonic (relaxed, comfort loving, sociable, peaceful)	Highly developed and massive visceral structure; buxom

TABLE A.2: SHELDON'S BODY TYPES [NEILL, 1999]

A.2 Freud's Psychoanalytic Perspective

ID (unconscious)	Most primitive portion of the personality - contains biological urges or instinctual motivation
	Focus of the id is to obtain immediate gratification: the pleasure principle
	Operations of the id are unconscious
	Seat of aggression and libido
EGO (partly conscious)	The ego searches for objects to satisfy the wishes that id creates with the restrictions of outer reality, thus obeying the reality Principle where the aim is to preserve the organism's integrity by withholding gratification until the desired object is found.
	Represents reality and reason
SUPEREGO (partly conscious)	The superego represents the moral guide and society (influences the ego)
	Two aspects to the superego: the first is the conscience, which is an internalization of punishments and warnings. The second is the "ego ideal". It derives from rewards and positive models presented to a child. The conscience and ego ideal communicate their requirements to the ego with feelings like pride, shame, and guilt

TABLE A.3: FREUD'S PSYCHOANALYTIC PERSPECTIVE OF PERSONALITY

A.3 Humanism Theories

A.3.1 Maslow

[Boeree, 1997; Bull, 2000; HP603, 1999]

Maslow's hierarchy of from top to bottom is:

1. Self–actualisation
2. Aesthetic needs: symmetry
3. Cognitive needs: to know, understand.
4. Esteem needs:
    - Lower: the need for the respect of others, the need for status, fame, glory, recognition, attention, reputation, appreciation, dignity, even dominance
    - Higher: the need for self-respect, including such feelings as confidence, competence, achievement, mastery, independence, and freedom.
5. Belonging and love needs: the need for friends, a sweetheart, children, etc.
6. Safety needs: interested in finding safe circumstances, stability, and protection
7. Physiological needs: hunger, thirst, to be active, to rest, to sleep

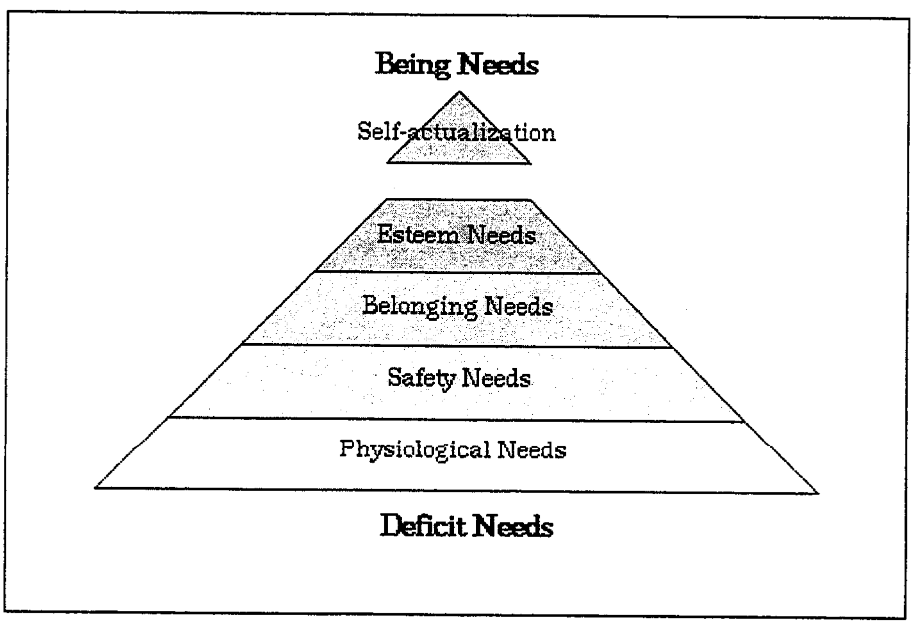


FIGURE A.1: MASLOW'S HIERARCHY OF NEEDS [BOEREE, 1997]

A.3.2 Rogers

[Boeree, 1997; Bull, 2000; HP603, 1999]

Elements of Rogers' "self" theory are:

- Self-Concept - how we see ourselves
- Positive Regard - acceptance, approval, love, positive feedback from important others
- Positive Self Regard - self-esteem, self-worth, a positive self-image
- Real Self versus Ideal Self – "I am" versus "I should"
- Mirror-Self - how we think others see us.
- Positive self-concept and self-fulfillment are most likely in a genuine, accepting, and empathic environment.

A.4 Behaviour Theory - Skinner

[Baldes, 2000; Boeree, 1997; Bull, 2000]

Tests conducted with rats in cages (Skinner's boxes) showed the influences of reinforcing and aversive stimuli, schedules of reinforcement, and shaping behaviours. Application of stimuli generates these results:

- A behaviour followed by a reinforcing stimulus results in an increased probability of that behaviour occurring in the future.
- A behaviour no longer followed by the reinforcing stimulus results in a decreased probability of that behaviour occurring in the future.
- A behaviour followed by an aversive stimulus results in a decreased probability of the behaviour occurring in the future.
- Behaviour followed by the removal of an aversive stimulus results in an increased probability of that behaviour occurring in the future.

Shaping deals with the issue of complex behaviour. It is a method of "successive approximation" involving a series of steps. First, a behaviour only distantly related to the one desired is reinforced. Once that is established, subsequent behaviour variations are refined through successive reinforcement. (Teaching pigeons to bowl.) Skinner's work has led to the modern therapy techniques with respect to behaviour modification or "b-mod". Eliminate an undesirable behaviour and replace it with a desirable behaviour by reinforcement methods.

A.5 Social Cognitive Theories

A.5.1 Mischel

Mischel's five broad "person variables" (as opposed to traits or dispositions) that he considered central to study of personality are:

- Competencies:
    - Overt and covert behaviours (knowledge and skills) a person is able to perform when required.
- Encoding strategies & personal constructs:
    - Ways of sorting, categorizing and representing knowledge and perceptions of physical events.
- Expectancies:
    - Probability estimates about outcomes of particular courses of action in particular situations.
- Personal / Subjective values:
    - Worth of possible outcomes of action.
    - Parallels Rotter's notion of reinforcement value.
- Self-regulatory systems & plans:
    - Self-imposed standards, goal and rewards of an individual.
    - Provides motivation and direction for behaviour.

A.6 Trait Theories

A.6.1 Cattell's 16 Universal Traits

#			
1	Reserved	versus	Warm
2	Concrete-reasoning	versus	Abstract-reasoning
3	Reactive	versus	Emotionally stable
4	Deferential	versus	Dominant
5	Serious	versus	Lively
6	Expedient	versus	Rule-conscious
7	Shy	versus	Socially-bold
8	Utilitarian	versus	Sensitive
9	Trusting	versus	Vigilant
10	Practical	versus	Imaginative
11	Forthright	versus	Private
12	Self-assured	versus	Apprehensive
13	Traditional	versus	Open to change
14	Group-oriented	versus	Self-reliant
15	Tolerates disorder	versus	Perfectionist
16	Relaxed	versus	Tense

TABLE A.4: CATTELL'S 16 UNIVERSAL TRAITS [NEILL, 1999]

A.6.2 Eysenck's Supertraits

Hans Eysenck developed a two-factor model consisting of "supertraits". Eysenck's two unique factors are:

- Extraversion
- Neuroticism (emotional stability)

Eysenck argued that these traits were associated with biological differences; hence, the seat of personality function is in the central nervous system. One representation extended a combination of Eysenck's supertraits to explain the 'Greek humours', listed below.

	Stable	Unstable
Introverted	Phlegmatic Calm	Melancholic Pessimistic *Susceptible to depression and anxiety*
Extraverted	Sanguine Optimistic	Choleric Irritable *Susceptible to sociopathy, antisociality*

TABLE A.5: EYSENCK'S SUPERTRAITS [NEILL, 1999]

A.6.3 Costa and McCrae: OCEAN Traits

[from Baldes, 2000]

The following tables reflect the positive and negative effects of the various facets, and the "type" of facets, which are reflected with various personality types/

Openness

(Explorer, Preserver, Moderate)

The Six Facets of Openness (adapted from Costa & McCrae, 1992)

Six Facets of Openness	**PRESERVER O-**	**EXPLORER O+**
Fantasy	Focuses on here and now	Imaginative; daydreams
Aesthetics	Uninterested in art	Appreciates art and beauty
Feelings	Ignores and discounts feelings	Values all emotions
Actions	Prefers the familiar	Prefers variety; tries new things
Ideas	Narrower intellectual focus	Broad intellectual curiosity
Values	Dogmatic; conservative	Open to re-examining values

TABLE A.6: THE SIX FACETS OF OPENESS [BALDES, 2000]

Conscientiousness

(Focused, Flexible, Balanced)

The Six Facets of Conscientiousness (adapted from Costa & McCrae, 1992)

Six Facets of Conscientiousness	**FLEXIBLE C-**	**FOCUSED C+**
Competence	Often feels unprepared	Feels capable and effective
Order	Unorganized unmethodical	Well-organized; neat; tidy
Dutifulness	Casual about obligations	Governed by conscience; reliable
Achievement Striving	Low need for achievement	Driven to achieve success
Self-Discipline	Procrastinates; distracted	Focused on completing tasks
Deliberation	Spontaneous; hasty	Thinks carefully before acting

TABLE A.7: THE SIX FACETS OF CONSCIENTIOUSNESS [BALDES, 2000]

Extraversion

(Extravert, Introverts, Ambiverts)

The Six Facets of Extraversion (adapted from Costa & McCrae, 1992)

Six Facets of Extraversion	**INTROVERT E-**	**EXTRAVERT E+**
Warmth	Reserved; formal	Affectionate; friendly, intimate
Gregariousness	Seldom seeks company	Gregarious, prefers company
Assertiveness	Stays in background	Assertive; speaks up; leads
Activity	Leisurely pace	Vigorous pace
Excitement-Seeking	Low need for thrills	Craves excitement
Positive Emotions	Less exuberant	Cheerful; optimistic

TABLE A.8: THE SIX FACETS OF EXTRAVERSION [BALDES, 2000]

Agreeableness

(Adapter, Challenger, Negotiator)

The Six Facets of Agreeableness (adapted from Costa & McCrae, 1992)

Six Facets of Agreeableness	**CHALLENGER A-**	**ADAPTER A+**
Trust	Cynical; sceptical	See others as honest and well-intentioned
Straightforwardness	Guarded; stretches truth	Straightforward, frank
Altruism	Reluctant to get involved	Willing to help others
Compliance	Aggressive; competitive	Yields under conflict; defers
Modesty	Feels superior to others	Self-effacing; humble
Tender-Mindedness	Hard headed; rational	Tender-minded; easily moved

TABLE A.9: THE SIX FACETS OF AGREEABLENESS [BALDES, 2000]

Neuroticism

(Reactive, Resilients, Responsives)

The Six Facets of Negative Emotionality (adapted from Costa & McCrae, 1992)

Six Facets of Negative Emotionality	**RESILIENT N-**	**REACTIVE N+**
Worry	Relaxed; calm	Worrying; uneasy
Anger	Composed; slow to anger	Quick to feel anger
Discouragement	Slowly discouraged	Easily discouraged
Self-Consciousness	Hard to embarrass	More easily embarrassed
Impulsiveness	Resists urges easily	Easily tempted
Vulnerability	Handles stress easily	Difficulty coping

TABLE A.10: THE SIX FACETS OF NEUROTICISM [BALDES, 2000]

APPENDIX B

B.1 IDEF0 Model

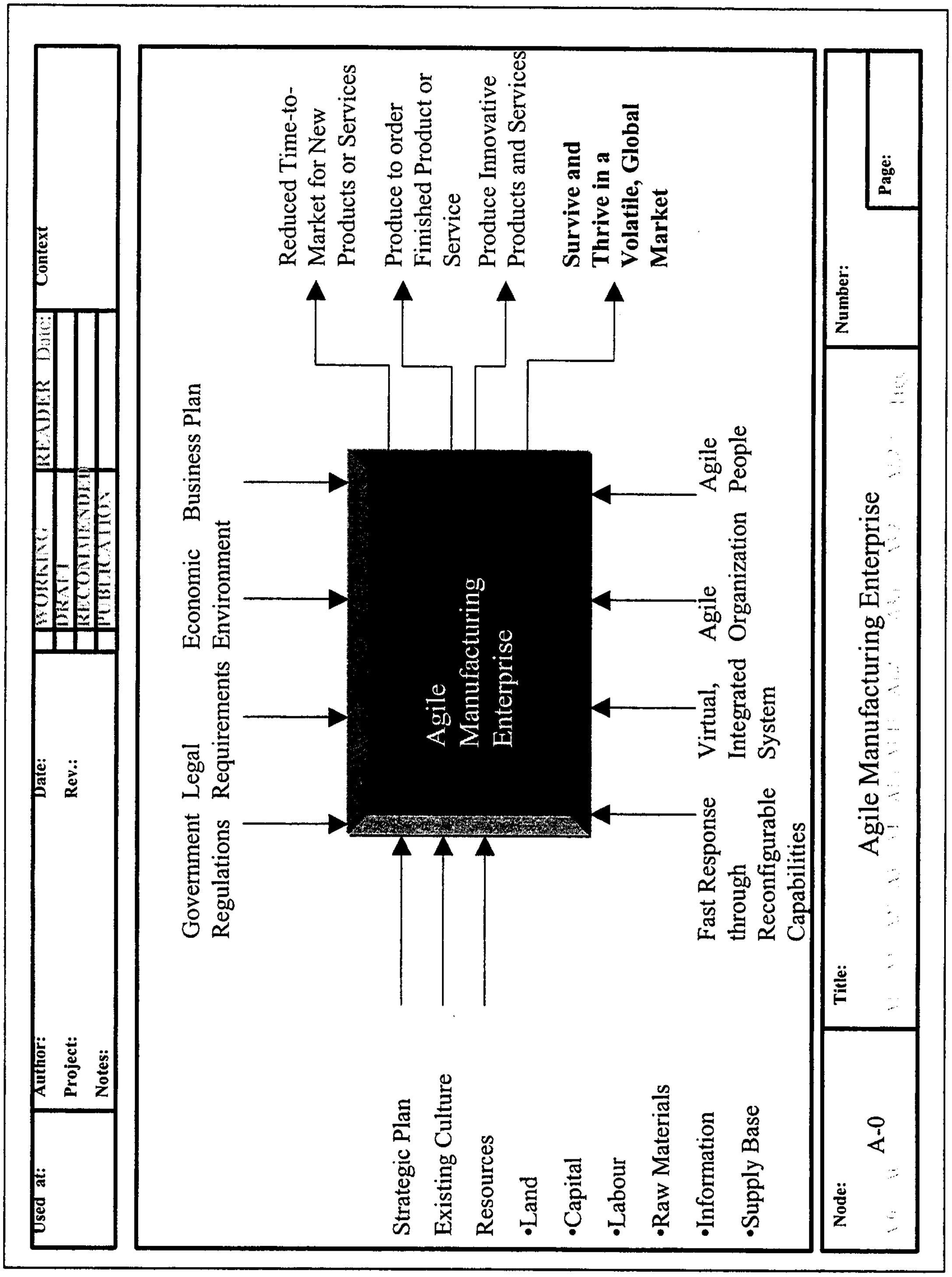


FIGURE B.1: IDEF0 MODEL NODE A-0

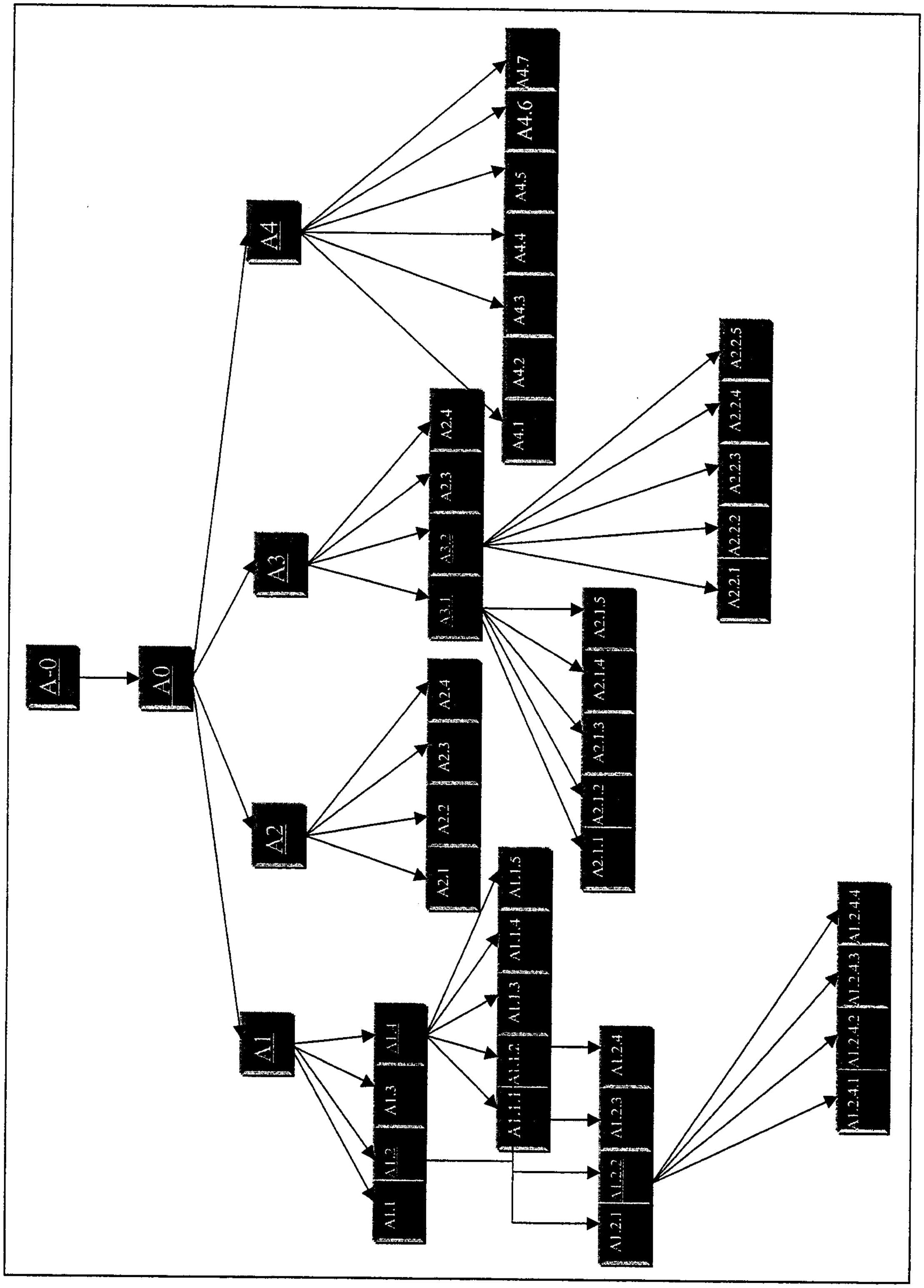


FIGURE B.2: IDEF0 MODEL NODES

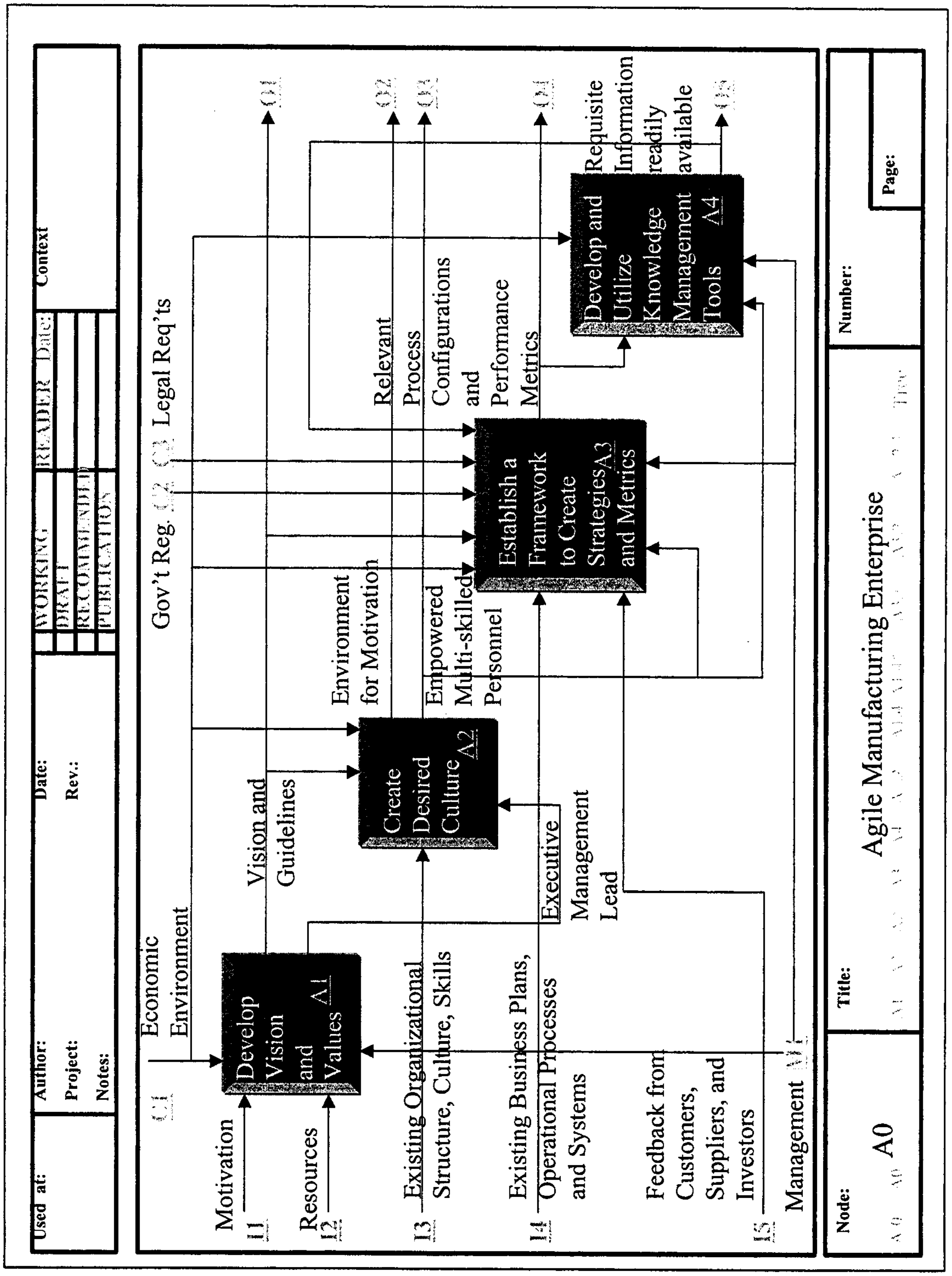


FIGURE B.3: IDEF0 MODEL NODE A0

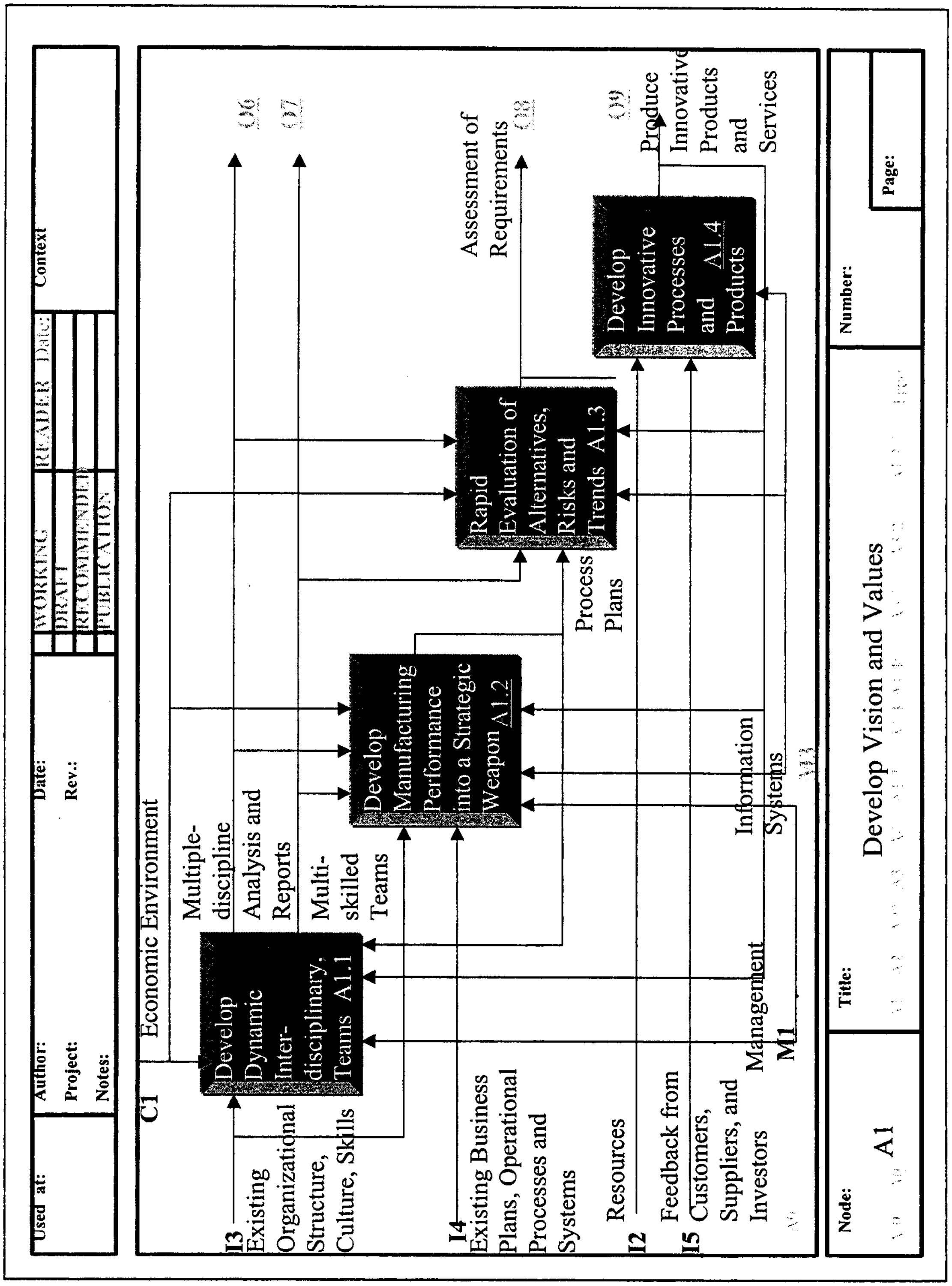


FIGURE B.4: IDEF0 MODEL NODE A1

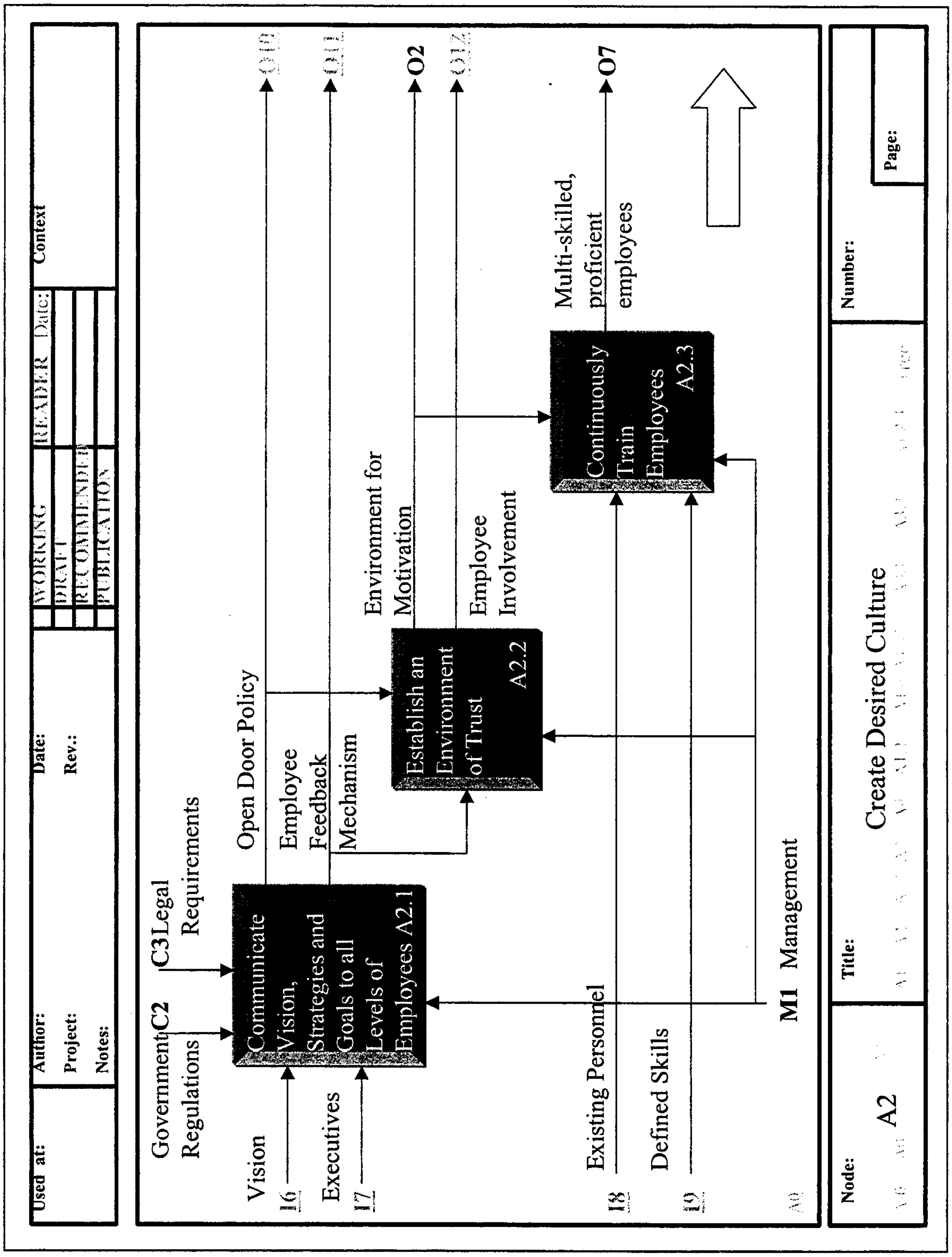


FIGURE B.5: IDEF0 MODEL NODE A2

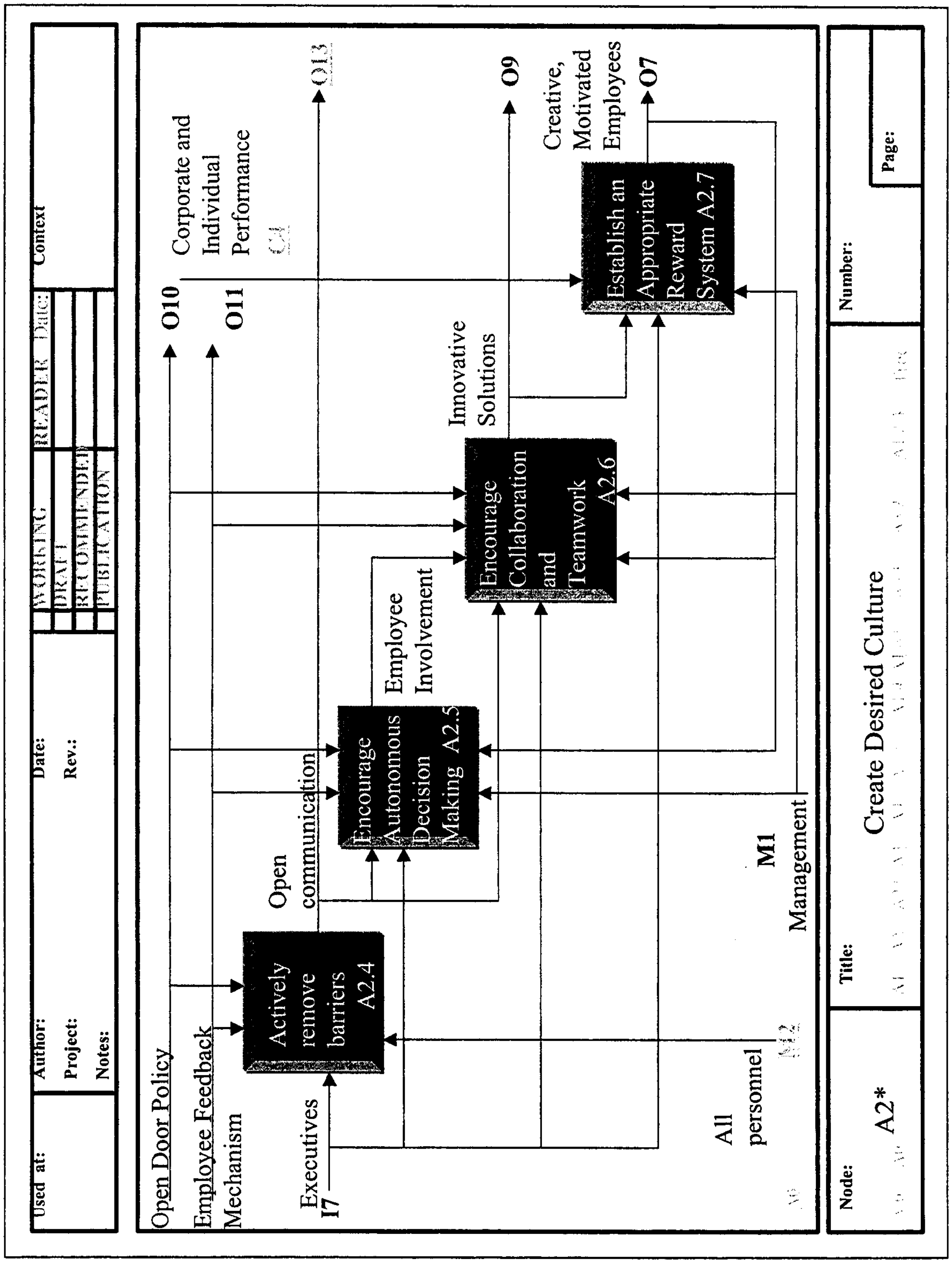


FIGURE B.6: IDEF0 MODEL NODE A2 CONTINUED

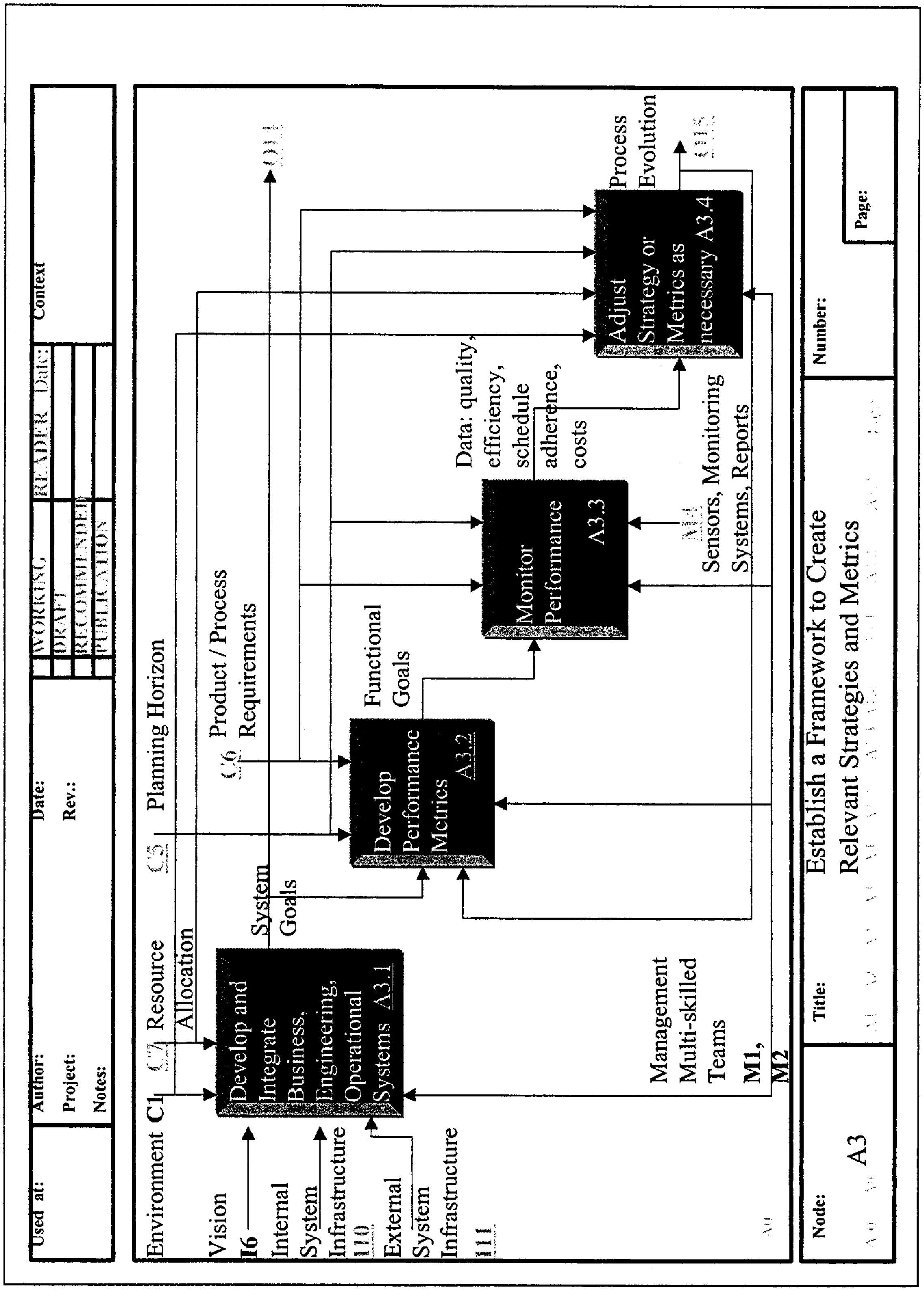


FIGURE B.7: IDEF0 MODEL NODE A3

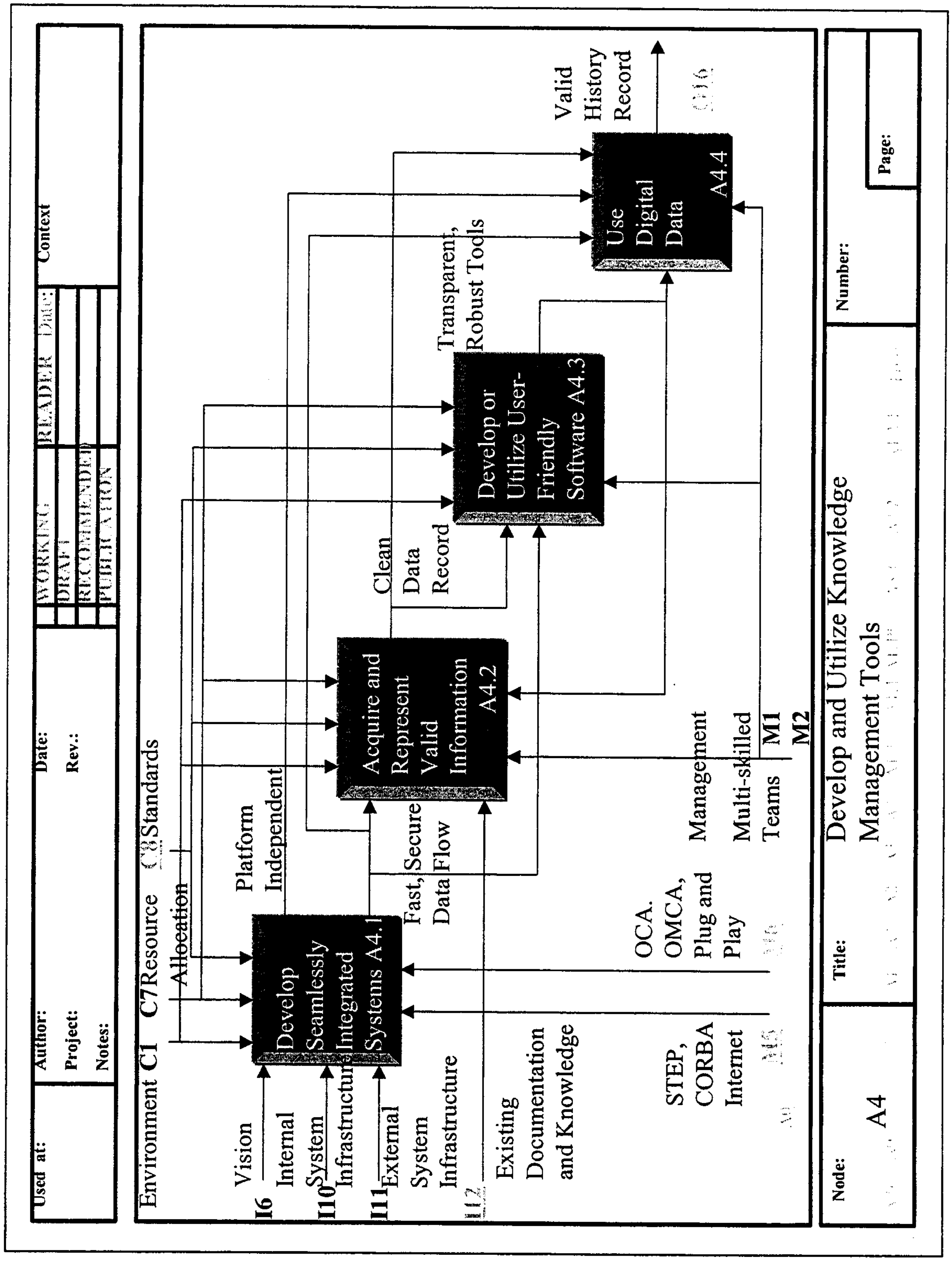


FIGURE B.8: IDEF0 MODEL NODE A4

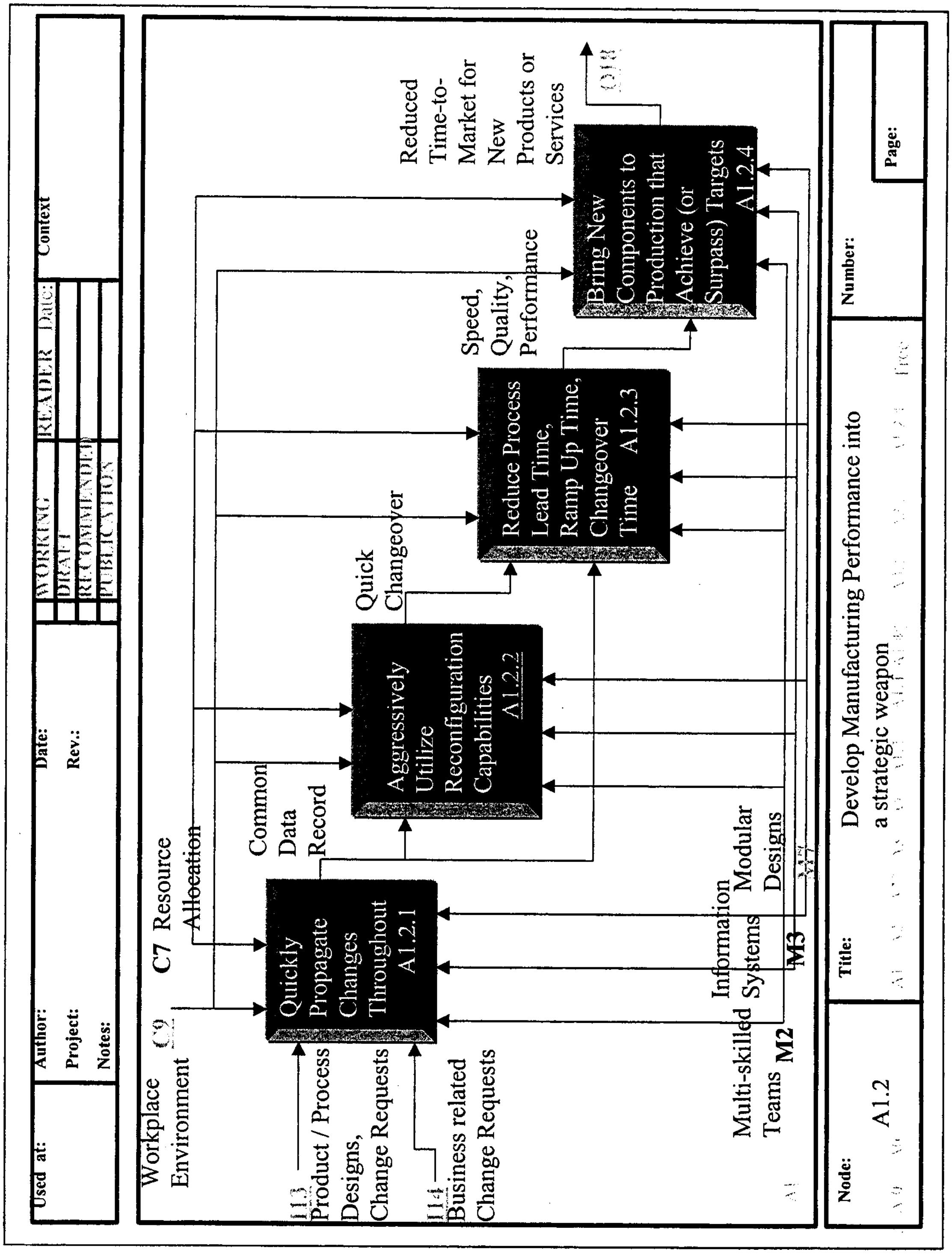


FIGURE B.9: IDEF0 MODEL NODE A1.2

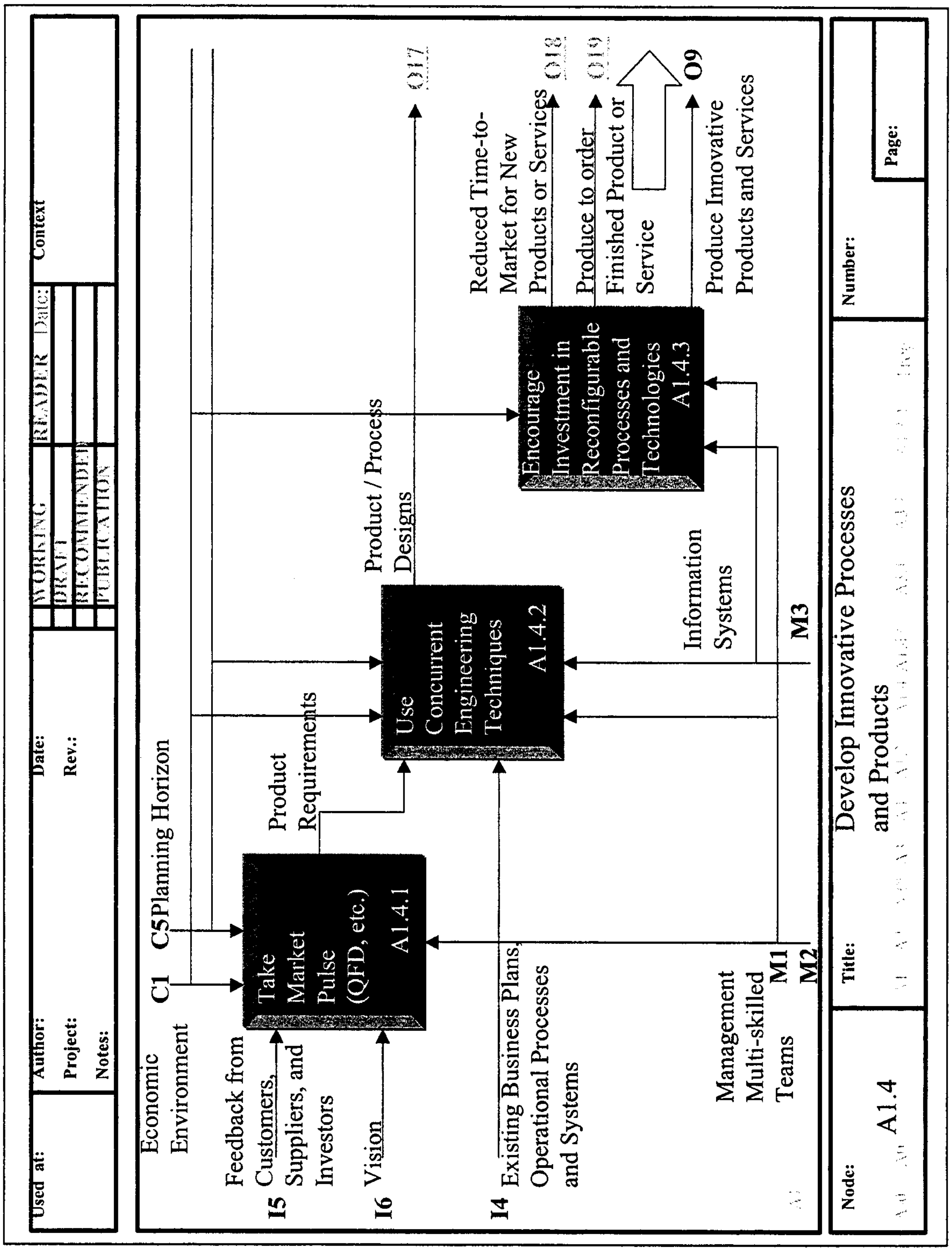


FIGURE B.10: IDEF0 MODEL NODE A1.4

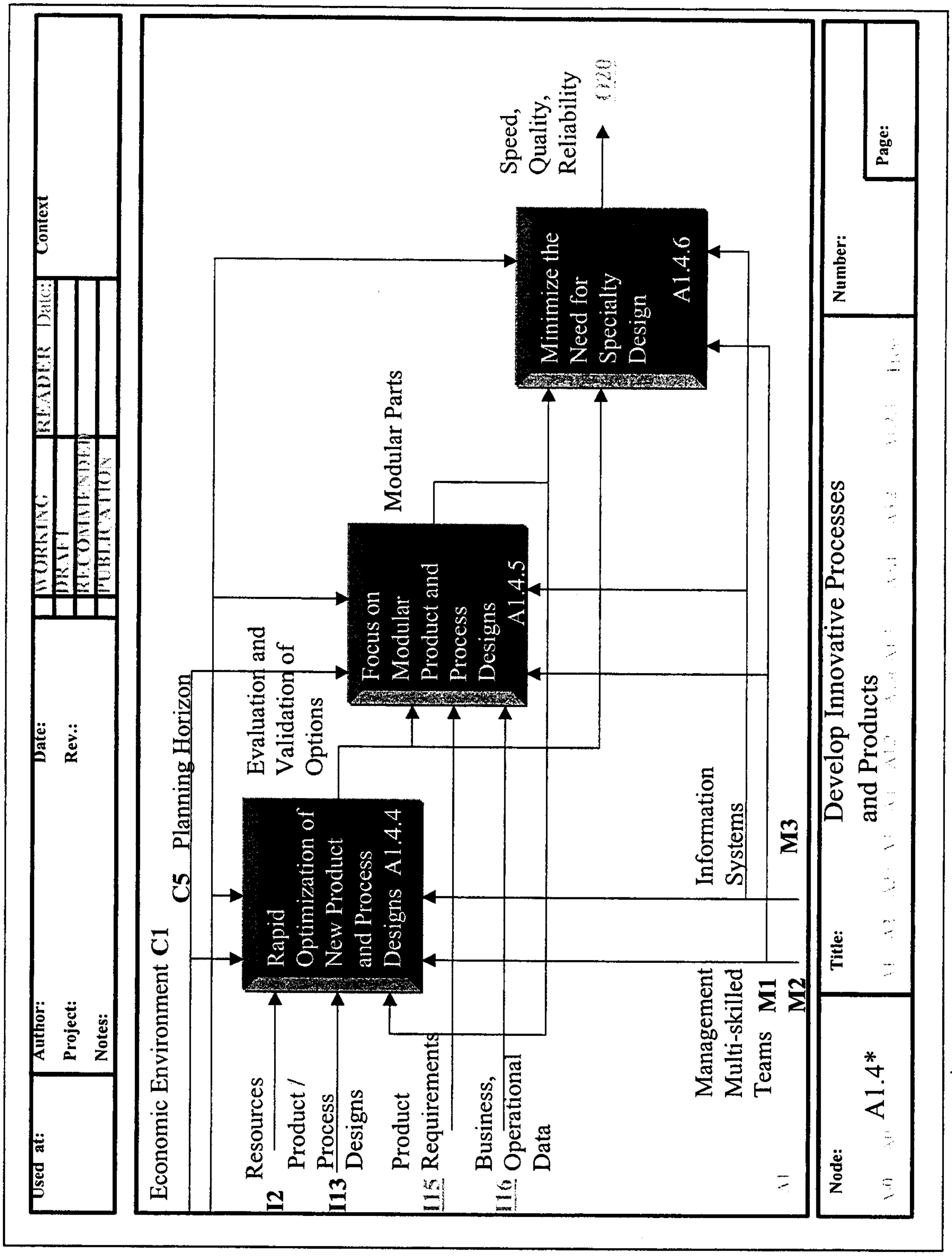


FIGURE B.11: IDEF0 MODEL NODE A1.4 CONTINUED

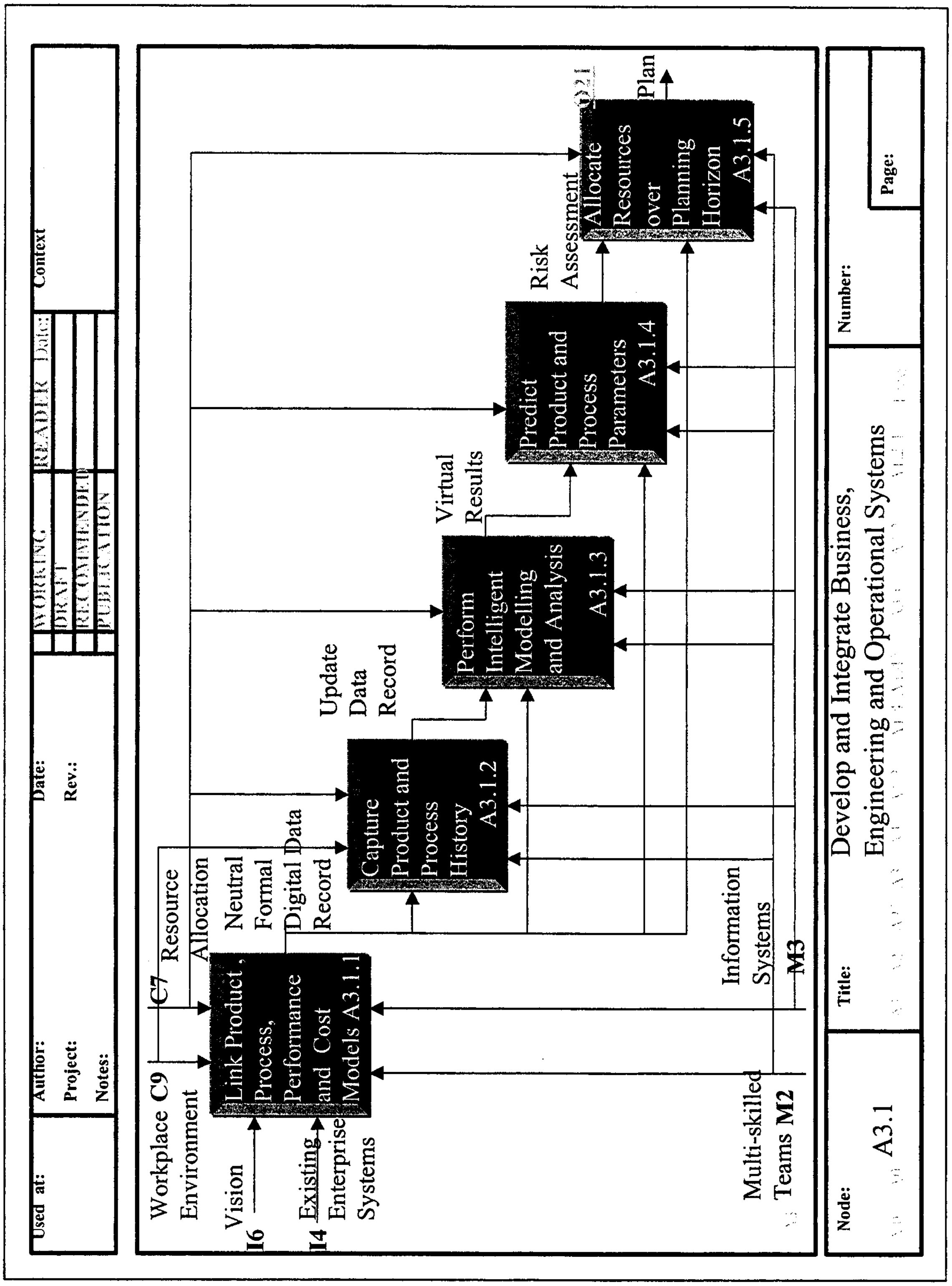


FIGURE B.12: IDEF0 MODEL NODE A3.1

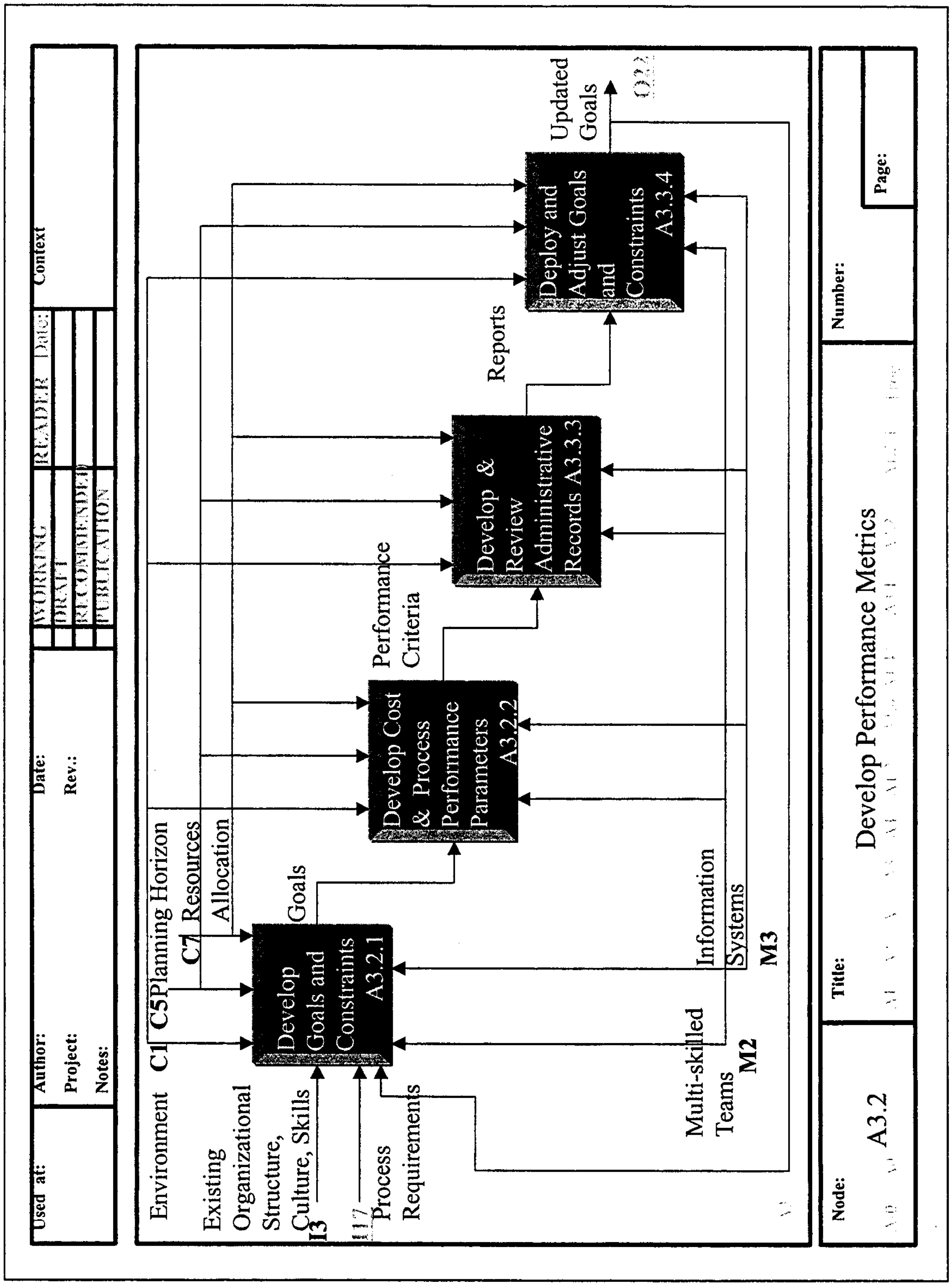


FIGURE B.13: IDEF0 MODEL NODE A3.2

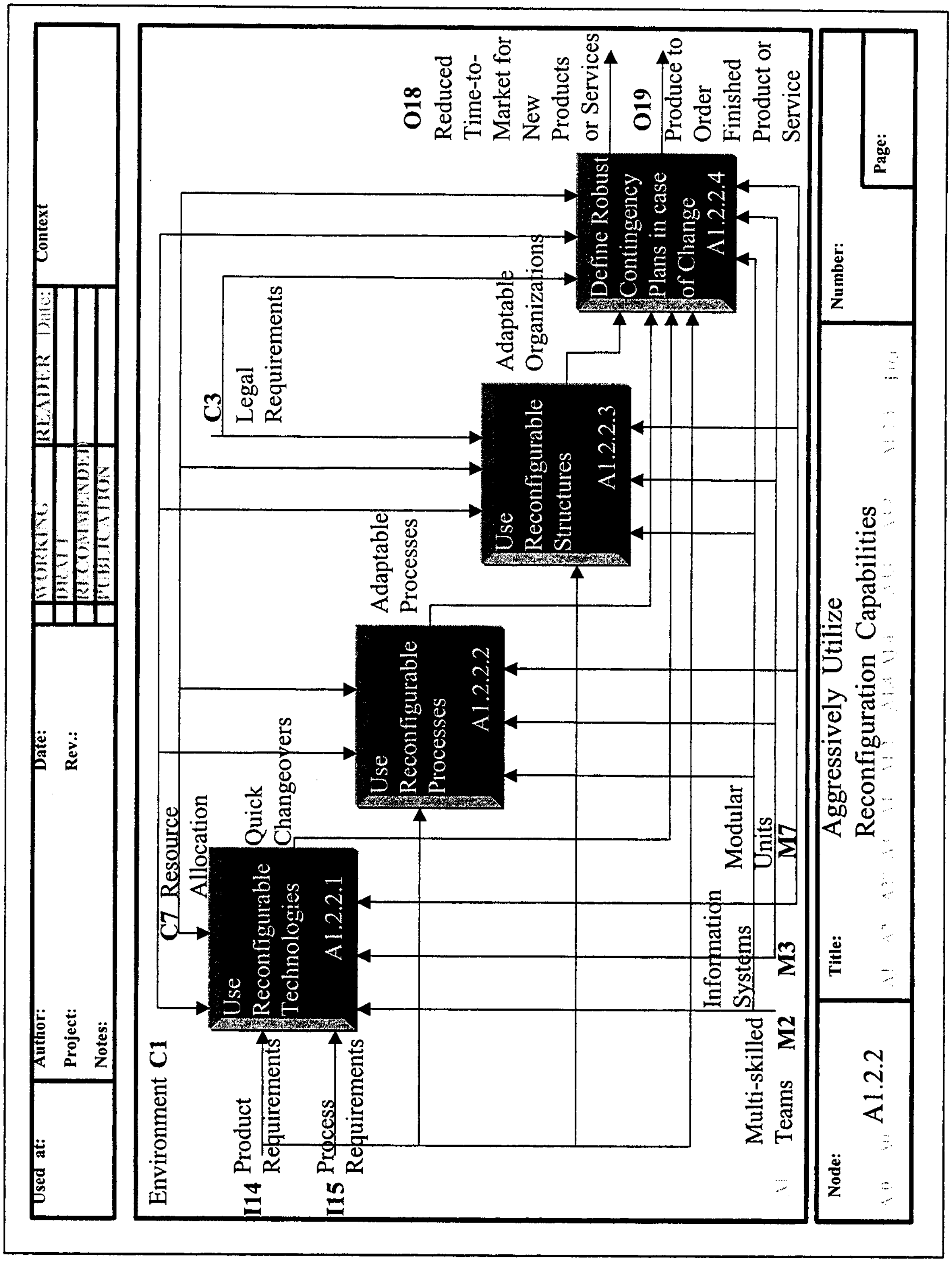


FIGURE B.14: IDEF0 MODEL NODE A1.2.2

APPENDIX C

The list of the power steering pump bracket features, the quantity of each feature and whether it is a final feature or contains in-process features is summarized in Table C.1.

Die Cast Al Steering Bracket		
Feature Description	Quantity	Feature or In-process
Location bosses -A-	3	F
Saddle	2	F
Circular Mouting surface	1	F
Curvelinear Mounting surface	2	F
Cross Plane Surface	1	F
Hole 1	1	F
Hole 2 (Cross Plane Hole) - tap	1	I/P
Hole 3 -tap	1	I/P
Hole 4 -B-	1	F
Hole 5 -C-	1	F
Hole 6	1	F
Hole 7 - tap	1	I/P
Hole 8 - tap	1	I/P
Hole 9A	1	I/P
Hole 9B	1	I/P
Hole 10 - tap	1	I/P
Hole 11	1	F
Hole 12 - tap	1	I/P
Hole 13- tap	1	I/P
Insert 2 bushings (9A&B)	2	F

TABLE C.1: POWER STEERING PUMP BRACKET FEATURE SUMMARY

The product complexity index $CI_{product} = 4.41$ for this example.

The generation of the product complexity coefficient is shown in Table C.2.

Description	Features J = 4							
		Diversity						
	Number	Material	Shape	Geometry	Tolerances	SUM	D/J	Feature
Location bosses -A-	3	0	0.5	0.5	0	1	0.25	0.75
Saddle	2	0	0	0	0	0	0.00	0
Circular Mouting surface	1	0	0	0	0	0	0.00	0
Curvelinear Mounting surface	2	0	0.5	0	0	0.5	0.13	0.25
Cross Plane Surface	1	0	0	0	0	0	0.00	0
Hole 1	1	0	0	0	0	0	0.00	0
Hole 2 (Cross Plane Hole) - tap	1	0	0	0	0.5	0.5	0.13	0.125
Hole 3 -tap	1	0	0	0	0	0	0.00	0
Hole 4 -B-	1	0	0.5	0.5	0.5	1.5	0.38	0.375
Hole 5 -C-	1	0	0.5	0.5	0.5	1.5	0.38	0.375
Hole 6	1	0	0.5	0.5	0	1	0.25	0.25
Hole 7 - tap	1	0	0	0	0.5	0.5	0.13	0.125
Hole 8 - tap	1	0	0	0	0	0	0.00	0
Hole 9A	1	0	0	0	0	0	0.00	0
Hole 9B	1	0	0	0	0	0	0.00	0
Hole 10 - tap	1	0	0	0	0	0	0.00	0
Hole 11	1	0	0.5	0.5	0.5	1.5	0.38	0.375
Hole 12 - tap	1	0	0	0	0	0	0.00	0
Hole 13 - tap	1	0	0	0	0	0	0.00	0
Insert 2 bushings (9A&B)	2	0	0	0	0	0	0.00	0
SUMS	25						2.00	2.625
Product Complexity Coefficient		0.105						

TABLE C.2: POWER STEERING BRACKET PRODUCT COMPLEXITY COEFFICIENT

The generation of the product information entropy H and diversity ratio D_R values are summarized in Table C.3

Description		Number	Diversity
Milled surfaces	position	8	5
	flatness	4	4
	perpend.	1	1
	surface finish	6	1
Hole 1	depth	1	1
	diameter	1	1
	position	1	1
Hole 4, 5	depth	2	0
	diameter	2	1
	position	2	2
Hole 6	depth	1	0
	diameter	1	1
	position	1	1
Hole 9A, 9B	depth	2	0
	diameter	2	1
	position	2	2
Hole 11	depth	1	0
	diameter	1	1
	position	1	1
Tapped holes	pitch	7	5
	cmfr depth	7	2
	depth	7	6
	% thrd	7	1
	position	7	7
Assembly	bushing	2	1
	alignment	2	1
SUM		79	47
H		6.30	
$D_{Rproduct}$			0.59

TABLE C.3: POWER STEERING PUMP BRACKET INFORMATION ENTROPY AND DIVERSITY

APPENDIX D

To illustrate calculating the operational complexity, the machining and assembly of the Mass Air Flow Body is used as an example. An overview of the product is shown in Figure D.1 and Table D.1, and the layout of the dedicated machining line is shown in Figure D.2, and summarized in Table D.2.

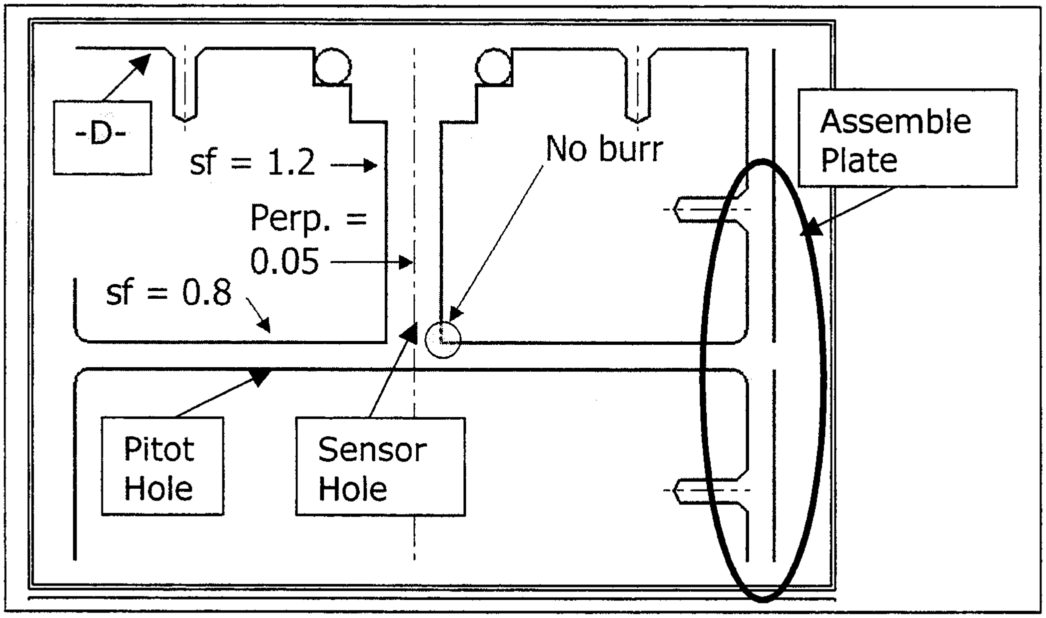


FIGURE D.1: MASS AIR FLOW BODY PRODUCT OVERVIEW

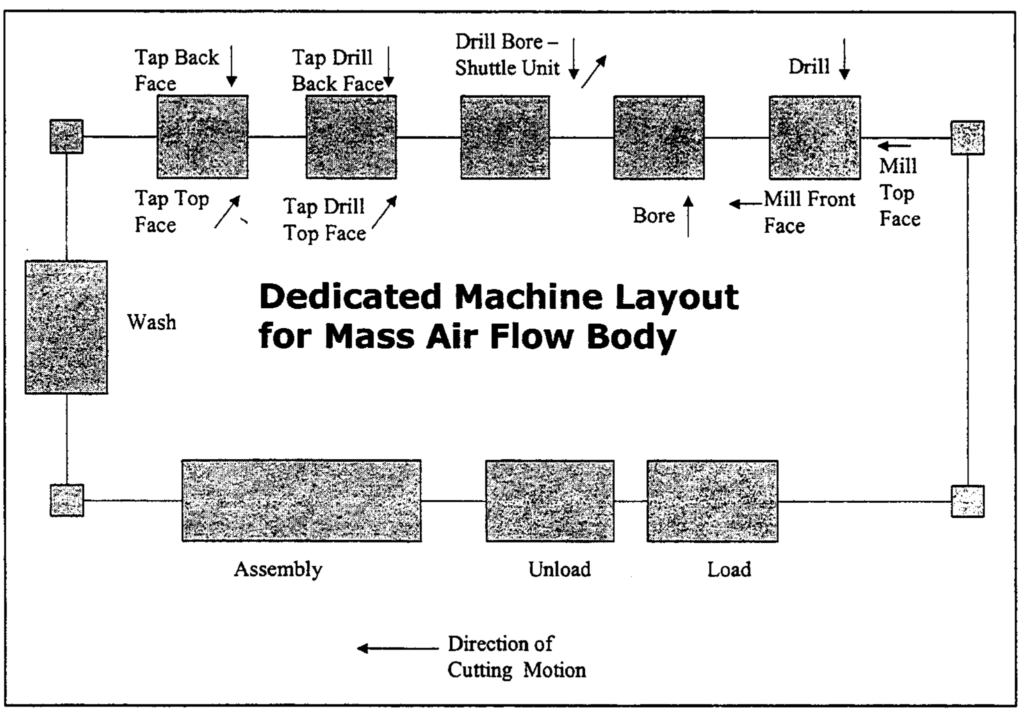


FIGURE D.2: LAYOUT OF THE MACHINING PROCESS FOR THE MASS AIR FLOW BODY

	Number	Mill	Drill	Tap	Bore
Front Face - Mill	1	4			
Sensor Face - Mill	1	4			
Sensor Mount Holes - drill, tap	2		8	8	
Plate Mount Holes - drill, tap	2		8	8	
Profile holes - drill, bore	2		8		16
Assemble Plate with 2 screws	1				
Amount per Pallet	4				
SUM		8	24	16	16

TABLE D.1: PRODUCT AND PROCESS OVERVIEW SUMMARY

	Orientation	Operation	Tools	No. of Tools	In-process Features
Station 1	Top	Load	manual		
	Front	Mill Front Face		1	
	Top	Mill -D-	multi insert mill	1	
Station 2	Back	Rgh Drill Pitot Hole	drill	4	x
Station 3	Front	Precision Bore Pitiot Hole	multi insert bore	4	
	Top	Rgh Drill Sensor Hole	step drill	4	x
Station 4	Top	Finish Bore Sensor Hole	multi insert bore	4	
	Top	Drill Sensor Mount Holes	3mm drill	4	x
Station 5	Back	Drill Plate Mount Holes	3mm drill	4	x
	Top	Tap Sensor Mount Holes	4mm tap	4	
Station 6	Back	Tap Plate Mount Holes	4mm tap	4	x
Station 7		Wash			
Station 8	Back	Assemble Plate	automatic		
Station 9	Top	Unload	manual		

TABLE D.2: PROCESS STATION AND OPERATION SUMMARY

The manufactured features and the product and process related tasked are tabulated in Tables D.3 and D.4 respectively. The values for the individual cells for a particular skill are generated from the relative effort analyses. The effort analysis associated with the tapped holes, drilled holes, bored holes, milled surfaces and the assembly are shown in Tables D.5 to D.9. As highlighted in Tables D.3 and D.4, the values for the operational complexity coefficients are: $c_{o,product} = 0.29$ and $c_{o,processt} = 0.30$.

	Tasks J = 4						
	Number	Product Skills					
		Setup Tools	Change Tools	Relation Gauge Features	Hand Gauge Features	SUM	D/J
Tapped holes	16	0.3	0.33	0.08	0.13	0.84	0.21
Drilled holes	24	0.3	0.5	0.25	0.25	1.3	0.33
Bored holes	8	0.52	0.48	0.33	0.33	1.66	0.42
Milled surfaces	8	0.22	0.37	0.25	0.08	0.92	0.23
Assembly	4	0	0.37	0	0.08	0.45	0.23

		Product
Tapped holes	16	**0.06**
Drilled holes	24	**0.13**
Bored holes	8	**0.06**
Milled surfaces	8	**0.03**
Assembly	4	**0.02**
SUM	60	**0.29**

TABLE D.3: PRODUCT RELATED SKILLS AND TASKS FOR EACH FEATURE

	Tasks K = 3					
	Number	Process Skills				
		Run Stations	Adjust Machines		SUM	D/J
			Mech.	Controls		
Tapped holes	2	0.08	0.47	0.25	0.8	0.27
Drilled holes	4	0.08	0.47	0.25	0.8	0.27
Bored holes	2	0.08	0.47	0.33	0.88	0.29
Milled surfaces	2	0.08	0.42	0.25	0.75	0.25
Assembly	2	0.47	0.53	0.33	1.33	0.44

		Process
Tapped holes	2	**0.04**
Drilled holes	4	**0.09**
Bored holes	2	**0.05**
Milled surfaces	2	**0.04**
Assembly	2	**0.07**
SUM	12	**0.30**

TABLE D.4: PROCESS RELATED SKILLS AND TASKS FOR EACH FEATURE

D.1 Tapped Holes Effort Analysis

Dedicated Pallet Machine: Tapped Holes

4 parts per pallet, 4 holes per part

Description	Physical M = 5							
	Number	Physical Environment			Labour			
		Temp	Cleanliness	Envelope	Strength	Dexterity	SUM	D/J
Setup Tools	16	0	0	0	0	0.5	0.5	0.10
Change Tools	16	0	0.5	1	0.5	0.5	2.5	0.50
Gage Features -r	4	0	0	0	0	0	0	0.00
Gage Features- h	4	0	0	0	0	0.5	0.5	0.10
Run Stations	2	0	0	0	0	0	0	0.00
Adjust - mech	2	0	0.5	1	0.5	1	3	0.60
Adjust - controls	2	0	0	0	0	0	0	0.00

Description	Cognitive Elements N = 3					
	Number	Cognitive				
		Procedures	In-process relationships	Performance Issues	SUM	D/J
Setup Tools	16	0.5	0.5	0.5	1.5	0.50
Change Tools	16	0	0	0.5	0.5	0.17
Gage Features -r	4	0.5	0	0	0.5	0.17
Gage Features- h	4	0	0	0.5	0.5	0.17
Run Stations	2	0	0.5	0	0.5	0.17
Adjust - mech	2	0	0.5	0.5	1	0.33
Adjust - controls	2	0.5	0.5	0.5	1.5	0.50

Description	Number	Effort
Setup Tools	16	0.30
Change Tools	16	0.33
Gage Features -r	4	0.08
Gage Features- h	4	0.13
Run Stations	2	0.08
Adjust - mech	2	0.47
Adjust - controls	2	0.25

TABLE D.5: TAPPED HOLES EFFORT ANALYSIS BASED ON THE PHYSICAL AND COGNITIVE ELEMENTS

D.2 Drilled Holes Effort Analysis

Dedicated Pallet Machine: Drilled Holes

4 parts per pallet, 6 in-process holes per part

Description	Physical M = 5							
	Number	Physical Environment			Labour			
		Temp	Cleanliness	Envelope	Strength	Dexterity	SUM	D/J
Setup Tools	24	0	0	0	0	0.5	0.5	0.10
Change Tools	24	0	0.5	1	0.5	0.5	2.5	0.50
Gage Features -r	6	0	0	0	0	0	0	0.00
Gage Features- h	6	0	0	0	0	0	0	0.00
Run Stations	4	0	0	0	0	0	0	0.00
Adjust - mech	4	0	0.5	1	0.5	1	3	0.60
Adjust - controls	4	0	0	0	0	0	0	0.00

Description	Cognitive Elements N = 3					
	Number	Cognitive				
		Procedures	In-process relationships	Performance Issues	SUM	D/J
Setup Tools	24	0.5	0.5	0.5	1.5	0.50
Change Tools	24	0.5	0.5	0.5	1.5	0.50
Gage Features -r	6	0.5	0.5	0.5	1.5	0.50
Gage Features- h	6	0.5	0.5	0.5	1.5	0.50
Run Stations	4	0	0.5	0	0.5	0.17
Adjust - mech	4	0	0.5	0.5	1	0.33
Adjust - controls	4	0.5	0.5	0.5	1.5	0.50

Description	Number	Effort
Setup Tools	24	0.30
Change Tools	24	0.50
Gage Features -r	6	0.25
Gage Features- h	6	0.25

Run Stations	4	0.08
Adjust - mech	4	0.47
Adjust - controls	4	0.25

Note: all drilled holes are in-process, added effort to retrieve partially machined parts, and reintroduce them into the line for finish machining

TABLE D.6: DRILLED HOLES EFFORT ANALYSIS BASED ON THE PHYSICAL AND COGNITIVE ELEMENTS

D.3 Bored Holes Effort Analysis

Dedicated Pallet Machine: Bored Holes

4 parts per pallet, 2 bored holes per part

Description	Physical M = 5							
	Number	Physical Environment			Labour			
		Temp	Cleanliness	Envelope	Strength	Dexterity	SUM	D/J
Setup Tools	8	0	0	0	0	1	1	0.20
Change Tools	8	0	0.5	0.5	0.5	0	1.5	0.30
Gage Features -r	2	0	0	0	0	0	0	0.00
Gage Features- h	2	0	0	0	0	0	0	0.00
Run Stations	2	0	0	0	0	0	0	0.00
Adjust - mech	2	0	0.5	1	0.5	1	3	0.60
Adjust - controls	2	0	0	0	0	0	0	0.00

Description	Cognitive Elements N = 3					
	Number	Cognitive				
		Procedures	In-process relationships	Performance Issues	SUM	D/J
Setup Tools	8	1	0.5	1	2.5	0.83
Change Tools	8	0.5	1	0.5	2	0.67
Gage Features -r	2	0.5	1	0.5	2	0.67
Gage Features- h	2	1	0.5	0.5	2	0.67
Run Stations	2	0	0.5	0	0.5	0.17
Adjust - mech	2	0	0.5	0.5	1	0.33
Adjust - controls	2	1	0.5	0.5	2	0.67

Description	Number	Effort
Setup Tools	8	0.52
Change Tools	8	0.48
Gage Features -r	2	0.33
Gage Features- h	2	0.33

Run Stations	2	0.08
Adjust - mech	2	0.47
Adjust - controls	2	0.33

Note: speciality tooling, in-line tool monitoring system

TABLE D.7: BORED HOLES EFFORT ANALYSIS BASED ON THE PHYSICAL AND COGNITIVE ELEMENTS

D.4 Milled Surfaces

Dedicated Pallet Machine: Milled Surfaces

4 parts per pallet; 2 milled surfaces per part, 2 large milling tools mill all surfaces in each plane

Description	Physical M = 5							
	Number	Physical Environment			Labour			
		Temp	Cleanliness	Envelope	Strength	Dexterity	SUM	D/J
Setup Tools	2	0	0	0	0	0.5	0.5	0.10
Change Tools	2	0	0.5	0.5	0.5	0.5	2	0.40
Gage Features -r	2	0	0	0	0	0	0	0.00
Gage Features- h	2	0	0	0	0	0	0	0.00
Run Stations	2	0	0	0	0	0	0	0.00
Adjust - mech	2	0	0.5	1	0.5	0.5	2.5	0.50
Adjust - controls	2	0	0	0	0	0	0	0.00

Description	Cognitive Elements N = 3					
	Number	Cognitive				
		Procedures	In-process relationships	Performance Issues	SUM	D/J
Setup Tools	2	0	1	0	1	0.33
Change Tools	2	0.5	0.5	0	1	0.33
Gage Features -r	2	0	1	0.5	1.5	0.50
Gage Features- h	2	0.5	0	0	0.5	0.17
Run Stations	2	0	0.5	0	0.5	0.17
Adjust - mech	2	0	0.5	0.5	1	0.33
Adjust - controls	2	0.5	0.5	0.5	1.5	0.50

Description	Number	Effort
Setup Tools	2	0.22
Change Tools	2	0.37
Gage Features -r	2	0.25
Gage Features- h	2	0.08

Run Stations	2	0.08
Adjust - mech	2	0.42
Adjust - controls	2	0.25

Note: milled surfaces are datum surfaces. hence care must be used for setup and final adjustments

TABLE D.8: MILLED SURFACES EFFORT ANALYSIS BASED ON THE PHYSICAL AND COGNITIVE ELEMENTS

D.5 Assembly Effort Analysis

Dedicated Pallet Machine: Milled Surfaces

4 parts per pallet, 1 plate and 2 screws assembled per part

Description	Physical M = 5							
	Number	Physical Environment			Labour			
		Temp	Cleanliness	Envelope	Strength	Dexterity	SUM	D/J
Setup Tools	8	0	0	0	0	0	0	0.00
Change Tools	8	0	0.5	1	0	0.5	2	0.40
Gage Features -r	2	0	0	0	0	0	0	0.00
Gage Features- h	2	0	0	0	0	0	0	0.00
Run Stations	2	0	0.5	0	0	0	0.5	0.10
Adjust - mech	2	0	0.5	1	0	0.5	2	0.40
Adjust - controls	2	0	0	0	0	0	0	0.00

Description	Cognitive Elements N = 3					
	Number	Cognitive				
		Procedures	In-process relationships	Performance Issues	SUM	D/J
Setup Tools	8	0	0	0	0	0.00
Change Tools	8	0.5	0.5	0	1	0.33
Gage Features -r	2	0	0	0	0	0.00
Gage Features- h	2	0.5	0	0	0.5	0.17
Run Machines	2	1	0.5	1	2.5	0.83
Adjust - mech	2	1	0.5	0.5	2	0.67
Adjust - controls	2	1	0.5	0.5	2	0.67

Description	Number	Effort
Setup Tools	8	0.00
Change Tools	8	0.37
Gage Features -r	2	0.00
Gage Features- h	2	0.08
Run Stations	2	0.47
Adjust - mech	2	0.53
Adjust - controls	2	0.33

Note: grayed out cells represent irrelevant categories for this function

TABLE D.9: ASSEMBLY EFFORT ANALYSIS BASED ON THE PHYSICAL AND COGNITIVE ELEMENTS

APPENDIX E

Human Characteristics' Utility Charts

Utility charts are used to plot the trends for the variables using normalized axes. The x-axis corresponds to a normalized task rate or normalized production rate. Each task or product has a standard time (t_{st}) associated with it. The normalized task rate is the standard time divided by the time to produce the first unit or generate the first task $p_t(i=1)$:

$$0 < \frac{t_{st}}{p_t(i=1)} \leq 1 \qquad \text{(E.1)}$$

The y-axis corresponds to five normalized indices (Product Diversity Index, Diversity Ratio, Product and Process Operational Complexity Coefficients, and the Effort Coefficient). Illustrations for these utility charts are shown in Figures E.1 to E.5.

E.1 Product Diversity Index

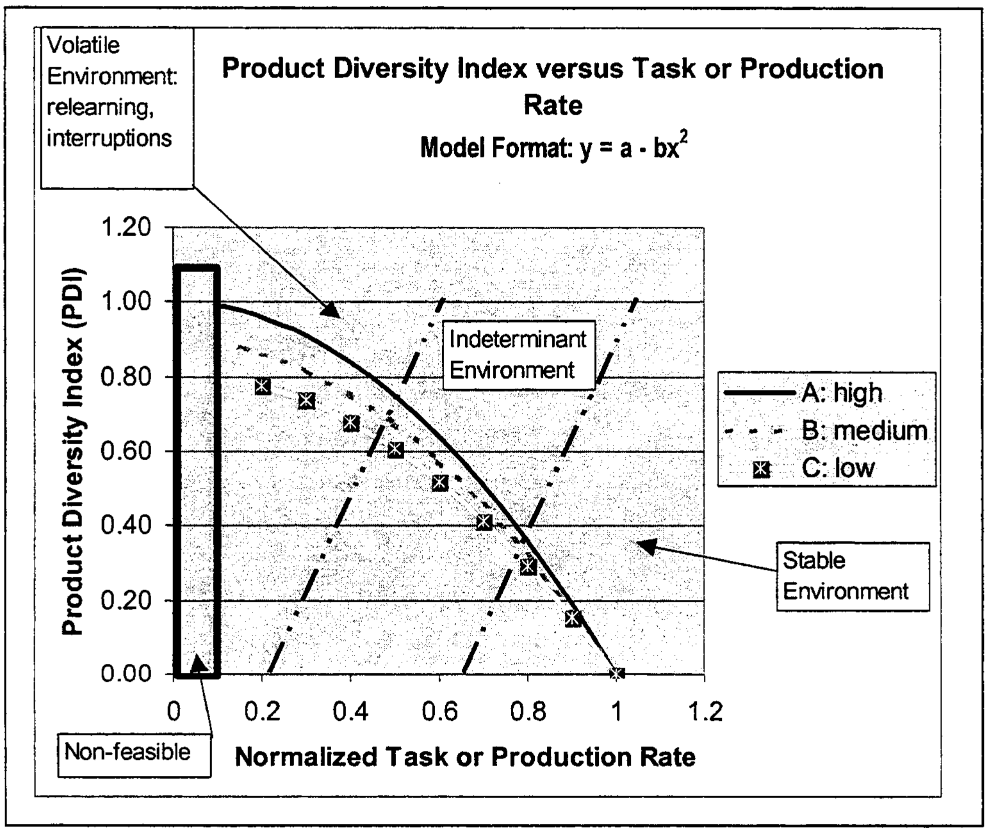


FIGURE E.1: UTILITY CHART - PRODUCT DIVERSITY INDEX

As the PDI → 0, there is very little product changeover. This is an indication of stable (repetitive) environment. Little variation exists; hence, the focus is on improving process efficiency and reducing waste. As the PDI → 1, constant changeovers occur. In this a very volatile environment, the focus is on quick changeovers and process throughput. Interruptions are constantly occurring, and the manufacturing process is never refined. There is an indeterminate zone, which is dependent on the environment and the product mix. If the skill and experience levels are not "good" throughput is not feasible. These zones are shown in Figure E.1.

E.2 Diversity Ratio

The amount and diversity of information associated with the product, process or operational complexity has an influence on both learning and productivity. The more diverse the information content (as $D_R \rightarrow 1$), the longer the time period or the number of task repetitions needed to assimilate the information or learn the new tasks. This has a direct impact on task rate, and is shown in Figure E.2.

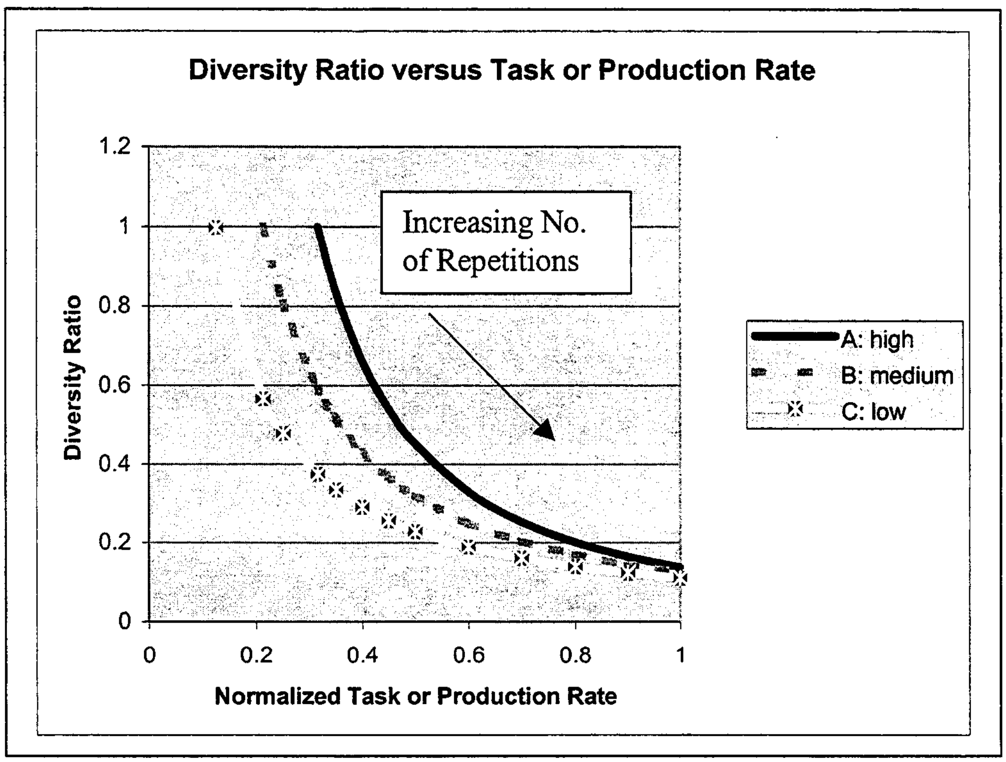


FIGURE E.2: UTILITY CHART – DIVERSITY RATIO

Level A corresponds to someone who has a high level of memory and learning skills; level B and C correspond to medium and low skills respectively. The general format of the curve should complement the "standard" learning curve described in Chapter 5 (equation 5.1).

E.3 Operational Complexity: Product and Process Complexity Coefficients

The trends for the complexity coefficients are assumed to be consistent for both the product and process operational complexity coefficients, as illustrated in Figure E.3.

Similar to the information content diversity, the more complexity associated with a task, the longer it takes to learn. The general format of the complexity curve should complement the "standard" learning curve described in Chapter 5 (equation 5.1) or the power law of practice (equation 6.8) described in Chapter 6.

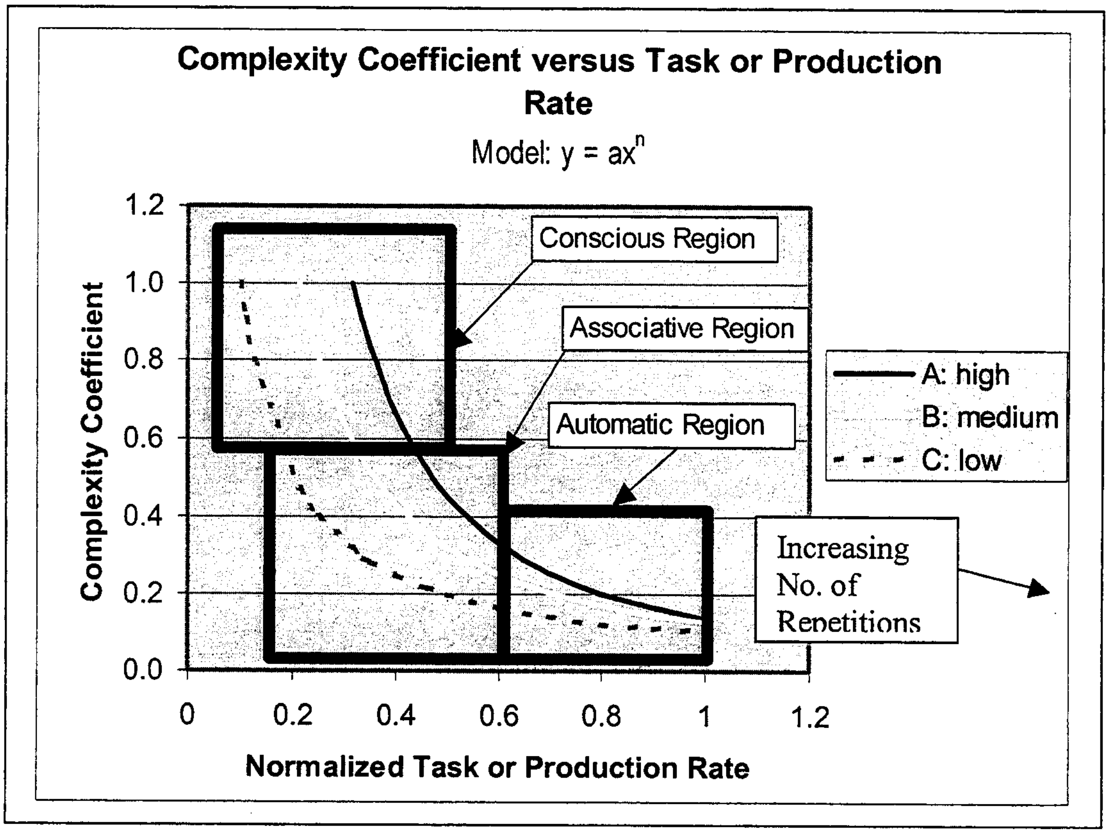


FIGURE E.3: UTILITY CHART – COMPLEXITY COEFFICIENT

As the operational complexity coefficients are interdependent with effort, the various regions depicted in Figure 7.30 are dynamic. The first time a task is performed, and it is a novel experience, conscious effort must be applied, as the knowledge base is expanding. Upon repetition (practice), skills and experience develop, and performance "rules" are created. Depending on the amount of task repetition and complexity, tasks may eventually be performed at the subconscious level, or automatically. A progression from conscious to automatic occurs; consequently, the fluctuating boundaries:

- Conscious region → new situation that previous experience (rules) or skills will not suffice → acquisition of new information and formulation of new rules
- Associative region → experience and skill is required for understanding → application of rules
- Automatic → subconscious level

The summary for the operational complexity coefficient is tabulated in Table E.1.

Level	**Comment**	**Equation**
A	High level of skill and experience AND no fatigue	$y = 0.14*x^{-1.72}$
B	Medium level of skill or experience OR **A** level skill but is experiencing fatigue	$y = 0.13*x^{-1.34}$
C	Low level of skill or experience OR **B** level skill but is experiencing fatigue	$y = 0.10*x^{-1.00}$

TABLE E.1: OPERATIONAL COMPLEXITY COEFFICIENT

E.4 Effort Coefficient

Each task has a physical and a cognitive aspect, and the effort coefficient is a normalized measure that reflects both aspects. The calculation of the effort coefficient serves as the basis for the process and product based operational complexity coefficient; hence, the effort coefficient represents the lowest level of analysis.

It is assumed that either a power equation format or a ln-linear format should be used for the utility char, illustrated in Figure E.4. The regions indicating conscious, associative and automatic are relevant for the effort coefficient as well, and they fluctuate based on skill and experience acquisition.

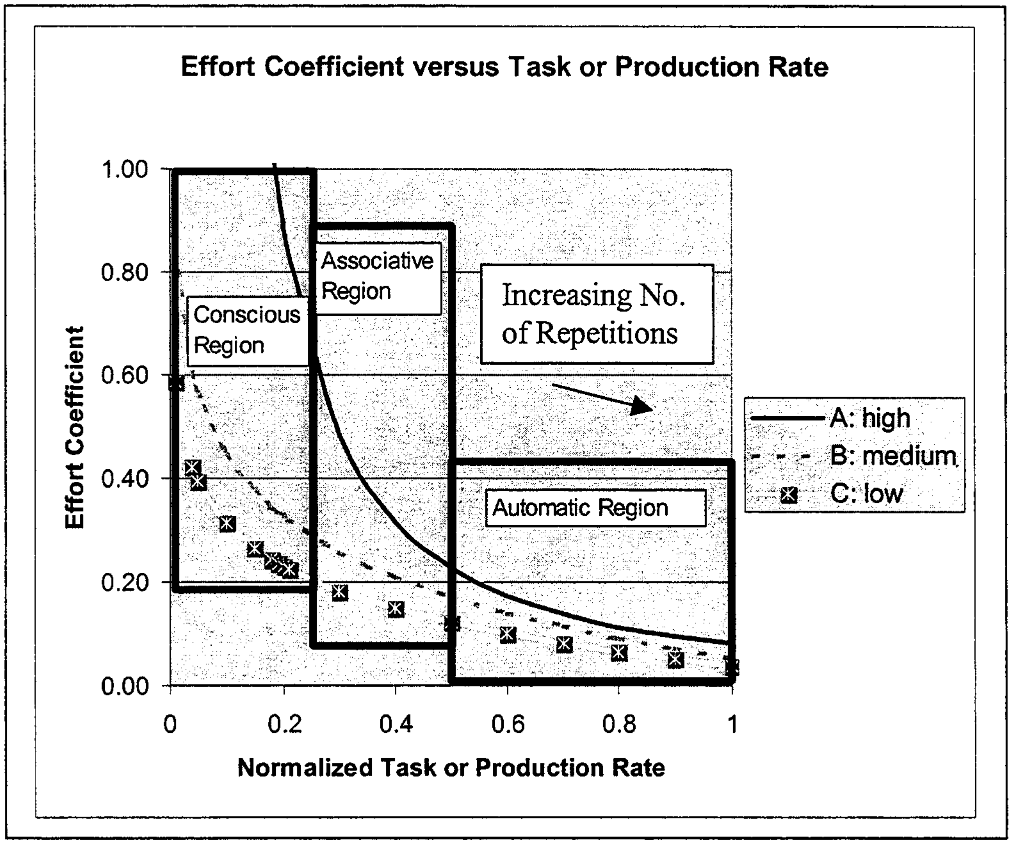


FIGURE E.4: UTILITY CHART - EFFORT COEFFICIENT

If the employee has poor or medium level skill sets, little experience, or is fatigued, the task cannot be performed if it requires extreme effort. To model this effect, a "ln-linear" equation format was used. A "power" equation format similar to the Complexity Coefficient versus Task Rate graph was used for level A. This is summarized in Table E.2.

Level	Comment	Equation
A	High level of skill and experience AND no fatigue	$y = 0.08*x^{-1.5}$
B	Medium level of skill or experience OR **A** level skill but is experiencing fatigue	$y = -0.17*LN(x)+0.055$
C	Low level of skill or experience OR **B** level skill but is experiencing fatigue	$y = -0.12*LN(x)+0.04$

TABLE E.2: EFFORT COEFFICIENT SUMMARY

E.5 Information Content

The information entropy measure is a scaling factor that acts on the diversity ratio and complexity measures to determine the complexity indices, but its effects also must be analyzed separately. The utility chart (Figure E.5) shows a linear relationship to the normalized task rate, as the entropy measure itself is a logarithm to the base 2. Simply stated, the greater the amount of information (product and process relationships, procedures, instructions, tools, etc.) the greater the impact on the initial task rate. (Note: 2^{10}=1024 pieces of information).

The final parameter that influences the task rate is the number of number of repetitions from the first time the task is performed until proficiency is reached. This is described by the standard learning curve (equation 5.1) or the power law of practice (equation 6.8). Figure E.6a illustrates the power law of practice. This is modified to reflect the accumulation of experience (or task rate improvement) in Figure E.6b.

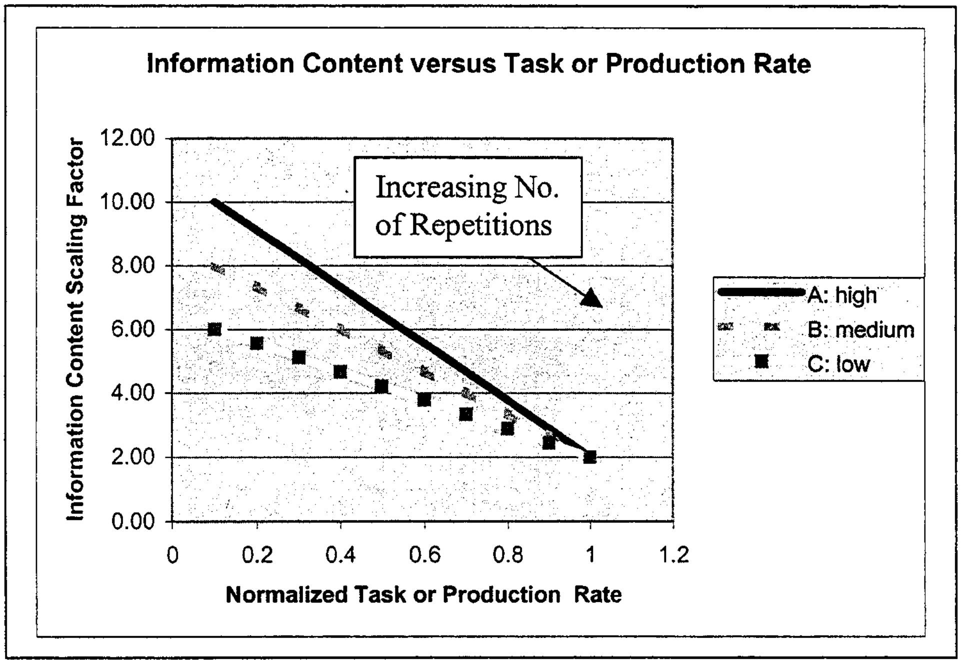


FIGURE E.5: UTILITY CHART: INFORMATION CONTENT

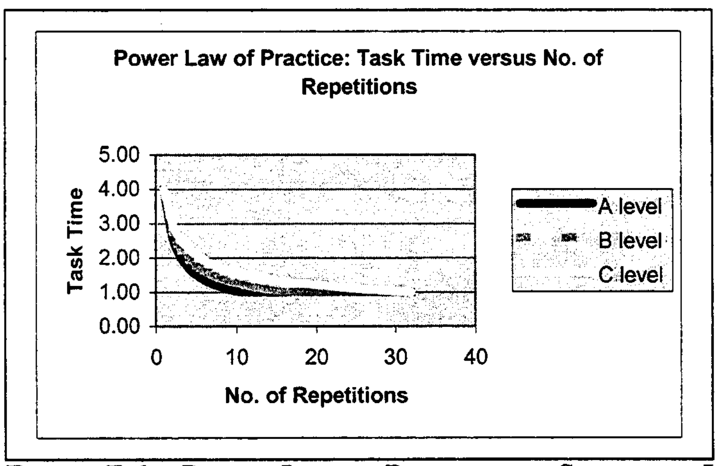


FIGURE E.6A: POWER LAW OF PRACTICE OR STANDARD LEARNING CURVE

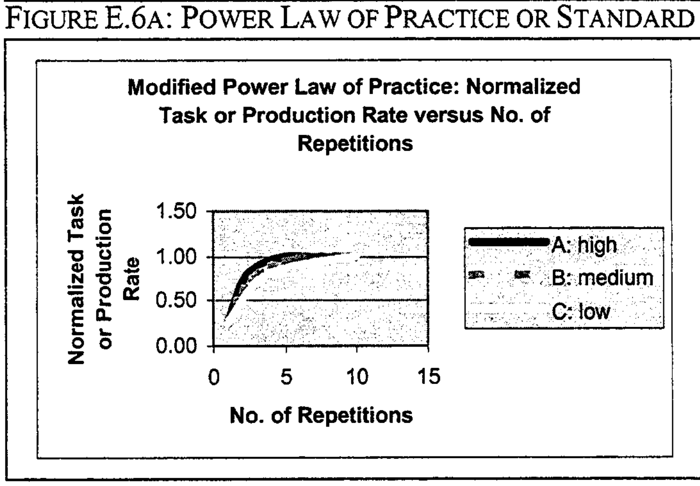


FIGURE E.6B: MODIFIED POWER LAW OF PRACTICE OR LEARNING CURVE

VITA AUCTORIS

NAME: R. Jill Urbanic

PLACE OF BIRTH: St. Catharines, Ontario, Canada

EDUCATION: University of Windsor, Windsor, Ontario

2001 – 2002 M. A. Sc.

University of Waterloo, Waterloo, Ontario

1980 – 1985 Hons. B. A. Sc.